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Essays on Finance: Drivers of Bank Performance and The International Cost of Equity

Johannes Arie Cornelis van Toor

Essays on Finance: Drivers of Bank Performance and The International Cost of Equity

Proefschrift

ter verkrijging van de graad van doctor aan Tilburg University op gezag van de rector magnificus, prof. dr. E.H.L. Aarts, in het openbaar te verdedigen ten overstaan van een door het college voor promoties aangewezen commissie in de aula van de Universiteit op vrijdag 15 december 2017 om 10.00 uur door

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geboren op 26 september 1989 te Zederik.

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	prof. dr. S.R.G. Ongena

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I imagine that climbing a mountain is a mix of extremes. On the one hand, it can be lonely and full of setbacks, such as lightning storms, dense fogs, and heavy rains. On the other, it is meditative, packed with spectacular views, and gratifying, once the summit has been reached. To me, this metaphor best describes how I look back on my PhD journey. At this point, I would like to thank the people who accompanied and supported me in my climb.

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Joris van Toor

November 6, 2017

Contents

1 Introduction

Banks serve to smooth out expenditures over time by transforming current savings into future spending and, vice versa, future income into current spending. Moreover, they are an essential pillar of a functioning payment system. The banking services of saving, lending, and payment facilitation are used by individuals, companies, governments, and all other economic entities, which implies that banks hold a pivotal position in the economy and society at large. This reliance on banks comes at a certain cost, however, in that it also makes the economy and society as a whole vulnerable to problems in the financial sector. The trade-off between the important role banks play in supporting the economy and their potential misuse of this pivotal position by taking excessive risks aroused my interest in how banks function. Stable, strong-performing banks are essential, but when their performance is not robust (e.g., because of a focus on short-term gains while neglecting long-term aims), they can become a liability and threat for society.

This latter situation was most clearly demonstrated by the recent financial crisis. The credit boom in the run-up to the crisis – driven primarily by an overheated mortgage market in the U.S. – led to strong stock market returns for banks, while the associated risks were hidden in the shadows of the regulated financial system. When trust evaporated and those risks materialized, it resulted in a modern-style bank run, thereby endangering the survival of banks. This forced governments to inject capital, grant loans, and provide guarantees to banks to avert financial and societal panic. Although the recent financial crisis was a major banking crisis, its occurrence is not unique: the U.S. has experienced 14 major banking crises in the last 180 years. These financial banking crises should be distinguished from other financial crises, such as the dotcom crisis of 2001, in which banks were unaffected. Financial banking crises inflict greater harm on the economy and society than other financial crises, in the form of increased budget deficits, loss of pension savings, rising unemployment, and a larger decline in economic growth.

This dissertation examines how the functioning of banks was related to their performance around the recent financial crisis in an attempt to understand the causes of the crisis and what we might be able to learn from it. It consists of four chapters. The first three focus mainly on the drivers of bank performance before, during, and after the financial banking crisis, and the fourth considers a firm's cost of equity in international markets, a firm characteristic that is crucial for banks when valuing firms and assessing their risk profile.

The first chapter focuses on the drivers of performance during the crisis for the 23 largest U.S. banks, which comprised approximately 70% of the U.S. banking sector. These banks are categorized as "weak" or "strong" banks, whereby I have defined strength as the ability to endure the crisis independently. Weak banks either went bankrupt, were acquired due to financial distress, or did not pass the stress test and needed government support. Strong banks, on the other hand, passed the test and repaid the government support as soon as they were allowed to. I argue that the strength of these banks was ultimately determined by their structure (i.e., formal governance) and the behavior of their CEOs and other employees. I compare the weak and strong banks on these dimensions for the period prior to the financial crisis (2002–2006). On the structural dimensions, I found that the quality of formal governance, as measured by CEO duality (i.e., when the CEO is also Chairman of the Board) and the rights of shareholders versus management, was slightly *lower* at strong banks. Hence, the formal governance structure did not prevent weak banks from needing a bailout or failing.

On the behavioral dimensions, I focus on the most powerful position within the bank, the Chief Executive Officer (CEO), and document that the CEOs of weak banks received higher cash bonuses and had a significantly higher incidence of having been raised in a low socioeconomic environment than their counterparts at strong banks. In addition, I investigate the financial riskiness of banks before the financial crisis. Although this has received much attention in the literature, I interpret it as the outcome of more fundamental structural and behavioral dimensions. Weak banks tended to be riskier than strong banks before the crisis in terms of funding risk (lower equity and higher debt), market risk (higher loans to assets ratio), and liquidity risk (more short-term debt). When this result is combined with the higher incidence of low-class CEOs at weak banks, it indicates a potential link between these variables. We must be careful, however, in interpreting this link. One interpretation could be that CEOs from a low-class background tend to more actively pursue risky practices than those from a high-class background because of an eagerness to show that in spite of their humble background, they are highly talented and no less capable than their elite colleagues. Alternatively, a CEO's personal influence on a bank's riskiness might be limited, with the latter resulting instead from a bank's organizational structure and behavioral culture and the interaction between these two factors over the decades. In that case, a risky bank might look for a CEO who fits into this risk culture, and that could be related to their low-class background.

Finally, I wonder about how the stock market perceived these two groups of banks around the time of the financial crisis. I therefore look at the buy-and-hold stock returns from January 2000 through February 2015. Weak banks outperformed strong ones in the run-up to the crisis by 113% but subsequently lost 94% of their market value in the crisis and did not recover to pre-crisis levels afterwards. Strong banks lost 71% of their market value, but their stock price is currently above pre-crisis levels. This suggests that weak banks took excessive risks before the crisis that resulted in them outperforming their strong counterparts, but when the crisis hit they were unable to withstand it independently.

In the second chapter, I wonder whether the negative relationship between performance before and after the crisis that I documented for large U.S. banks in Chapter 2 can be generalized to a larger sample of banks. That is, I search for an answer to the following question: Which banks failed to recover from the financial crisis and why? Although there has been much research into bank performance during the financial banking crisis, I am the first person, to the best of my knowledge, to consider the relationship between a bank's pre-crisis and post-crisis performance. I develop two possible hypotheses for that relationship: 1) the boom-and-bust hypothesis, which predicts a negative relationship between pre- and post-crisis stock returns and 2) the high risk–high reward hypothesis, which implies a positive relationship. I present strong support for the boom-and-bust hypothesis: that is, the best-performing U.S. banks before the crisis (2000 through December 2006) have been the worst performers since the crisis (March 2009 through 2015). Furthermore, high pre-crisis bank returns are associated with high riskiness. The evidence further suggests that the growth in loans was the main driver of excess returns before the crisis and has caused lagging returns since the crisis.

The literature on financial crises has documented that debt levels increase in the run-up to such a crisis. My finding addresses the other side of the same coin, namely that that debt is partly financed by excessive loan growth at the banks. Since the widespread extension of credit also led to a deterioration in the credit quality of the loans, this then produced a double problem for the banks when the tide turned: a general decline in loan performance, further exacerbated by an additional decline in the performance of low-credit-quality loans. As a result, these banks became bottom performers during and after the financial crisis. I argue that the high-performing U.S. banks pre-crisis were unable to fundamentally transform or adapt their risky business models afterwards and have therefore become post-crisis laggards.

As a final step, I analyze whether these findings can also be observed for European banks and found that the results were quite different: the best performers there from before the crisis (2000 through July 2007) continued to perform best afterwards (March 2009 through 2015). I have two potential explanations for this finding in Europe. First, consistent with the high risk–high reward hypothesis, European banks were able to once again reap the benefits of their risky practices after the crisis. Second, unlike their U.S. counterparts, strongly performing European banks have been less compelled to change their business model since the crisis, either because their practices were already more in line with the post-crisis requirements of the market and regulators or because they were given more time to adjust to the new environment.

In the third chapter, I depart from focusing on bank performance in relation to the financial banking crisis and consider instead the performance of banks in relation to CEO turnover, based on a study of a European cooperative bank over a 5-year period (2010–2015). This cooperative bank can be considered a strong bank according to the classification used in the first chapter; that is, it survived the financial crisis on its own. I use a panel data set with information on 106 local banks that are part of the cooperative. This sample provides a unique setting for testing whether and how CEO turnover matters for bank performance, in that it balances homogeneity (all banks were part of one organization) and heterogeneity (CEOs have considerable decision freedom). I present strong evidence that the return on assets significantly declines in the first year(s) after a CEO change.

Subsequently, I examine whether this decline in performance is the result of a change in CEO or whether, conversely, the change in CEO is the result of weak bank performance, measured as the return on assets (whereby the return equals net income minus the sum of operating costs and provisions for bad loans). I address this potential issue of reverse causality by using instrumental variable analysis and find support for the interpretation that the change in CEO has a negative impact on bank performance and not vice versa. When further analyzing the impact of a change in CEO on bank performance, I find that the decline in return on assets is caused by an increase in provisions for bad loans. Since there is no material impact on the bank's operating performance, alternative explanations such as a difference in quality between the predecessor and successor or new CEOs needing time to habituate to their new bank become less likely. Instead, by tracking the provisioning of bad loans in the years before and after a CEO change, I demonstrate that the increase in provisions in the first year of a new CEO can be explained by a combination of two underlying motives: 1) to offset a backlog in provisions on the part of the old CEO and 2) to ensure a position from which to boost results in the future through a subsequent decrease in provisions. Overall, the evidence indicates that newly appointed CEOs influence bank performance by adjusting the provisions for bad loans. Increases in provisions for bad loans are not harmless, since they reduce a bank's profitability and, as a consequence, its equity position. This, in its turn, reduces a local bank's room for providing loans. Moreover, an increase in impaired loans implies additional scrutiny of the borrower by the lender, which entails extra costs for both parties. I therefore recommend keeping a close eye on provisioning for bad loans around CEO changes.

The first three chapters empirically investigate the performance of the largest U.S. banks, a broad sample of U.S. and European banks, and one cooperative with over a hundred local banks. In the final chapter, the focus shifts to an activity banks perform to appropriately value companies, that is, the computation of a firm's cost of equity. This is a common practice in the corporate finance and asset management departments of banks, where they advise clients on potential mergers and acquisitions and profitable investments, respectively. It is also relevant for the banks' loan and risk management departments, since decisions related to extending loans and loan riskiness also depend on a firm's value. One of the indispensable factors in determining this value, equal to the discounted value of the firm's future cash flows, is the discount rate. This discount rate is composed of the weighted average cost of debt and equity, where the weighting is determined by the proportion of each variable in a company's total funding.

Whereas the cost of debt can be inferred from the required rate of return on the bonds a firm has issued, determining the cost of equity is less obvious. Despite criticism from academics, the Capital Asset Pricing Model (CAPM) is still the default model applied in practice to determine the cost of equity. In this model, the cost of equity is determined by the relationship between a company's stock return and a stock market index return. Although the acceleration of capital market integration would imply that a global market index should be used to determine the cost of equity, practitioners often still use a local index. I document that the use of a local index introduces a statistically and economically significant mistake in the cost of equity compared to using the correct global index. The analysis covers a nearly 20-year period (1996–2015) for developed countries, where the assumption of capital market integration is legitimate, and for BRIC countries, whose capital markets are becoming increasingly integrated with world capital markets. My findings show that the largest mistakes in the cost of equity occur for well-integrated countries with many globally operating companies (e.g., Switzerland), where global factors are the relevant pricing factors, while mistakes are small for segmented countries (e.g., China), where local factors are still the most relevant. Finally, the mistake increases from the first 10-year sub-period (1996–2005) to the second (2006–2015). I therefore conclude that the global version of the CAPM is increasingly becoming the most relevant model for cost of equity calculations.

I use a diverse range of empirical methods throughout this dissertation. In the first chapter, I primarily employ a univariate comparison of weak and strong banks on multiple dimensions, though multivariate analyses are performed using a discrete choice model (i.e., logit) to relate the banks' strength to governance, behavioral, and financial characteristics. In the second chapter, the relationship between bank performance before and after the financial crisis is analyzed using ordinary least squares for a cross section of U.S. and European banks. In the third chapter a panel data set is used to document a decline in bank performance in the first years after a change in CEO. This setup allows for controlling for effects that are the same for all banks in any given year (e.g., the impact of a nationwide decline in the economy) and for effects that differ between banks but are constant over time (e.g., the culture of local banks). Furthermore, I perform an instrumental variable analysis to analyze the causality of the main finding. In the final chapter, I employ ordinary least squares using time-series data to relate a firm's stock return to the returns of stock indices.

The first three chapters put the performance of banks before, during, and after the financial banking crisis at the center. This crisis had a significant impact on the public, which suffered a double blow: 1) the government's provision of bailout money to avert financial panic and 2) the economic contraction following the crisis. Although the U.S. economy has recovered quite rapidly, the recovery in some European countries is still fragile. The persistence of the economic recession there is reflected in the unemployment rate, for example, which peaked at 11% in early 2013 for Europe as a whole but remains above 15% for some European countries (i.e., Greece and Spain). Even more troubling for the long-term prospects of the Euro zone is the high youth unemployment rate, currently approximately 19%.[1] While other factors have also undoubtedly affected the recent unemployment rates in Europe, such as the Euro crisis and the fundamentally weaker economic conditions of various southern European countries, a common view amongst economists is that the financial crisis has had a severe, long-lasting impact on "the economy".

So, after having studied the financial banking crisis for the last four years, I would like to take the liberty of reflecting on the following question to finish up the introduction of my dissertation: Has the banking system become safer now than it was before the financial banking crisis, given all the measures that have been taken since? I will start by pointing to three conditions that jeopardized the stability of the financial system and society in the recent crisis. First, banks had the opportunity to take irresponsible risks, which means they were not sufficiently disciplined – not by their (non-executive) board

[1] See `http://ec.europa.eu/eurostat/statistics-explained/index.php/Main_Page` for the unemployment statistics.

members nor by the market nor by regulators nor by any other parties (accountants, journalists, public at large, works councils, etc.). Second, even if they were given the opportunity to take risks at the expense of the stability of the system, they did not have to do so; but they chose to benefit from regulatory flaws and weaknesses and thereby harmed their own customers and the stability of the system and society. Third, a final step that endangers the stability of society is when problems in the banking system spread to the economy/society at large. This occurred because banks had to be rescued by the government to avert financial panic and because of the subsequent economic recession.

In judging policy responses to this crisis, I organize them along the following three lines: 1) restricting the ability of banks to take excessive risks by increasing market and regulatory discipline, 2) ensuring proper behavior among bankers, and 3) restricting the negative consequences of problems in the banking sector. When the financial crisis started, the disciplinary actions of the providers of bank capital (i.e., shareholders, bondholders, and depositors) on the banks' activities were limited. Although shareholders experienced severe losses during the crisis, which had not been recuperated up to eight years after the crisis (see Chapter 3), they did not question the pre-crisis risk-taking by banks, potentially because they had been lured in by large returns. Moreover, bondholders and depositors, who were rewarded with lower returns, counted on the regulators and the government to rescue the banks if they experienced severe trouble. This safeguard pertained predominantly to large institutions, which dominated the scene having been formed through the wave of mergers and acquisitions in the decades before the crisis. The implicit too-big-to-fail guarantee, which became explicit during the crisis, might also have played a role in shareholders exerting less monitoring effort, because they did not expect that the government would allow large banks to go bankrupt. In order to restore the discipline of the market, providers of the banks' funding have to be convinced that banks can be liquidated in an orderly manner, whereby the losses will be absorbed by the providers of their funds. Since the stability in the financial system requires insurance of deposits up to a certain amount, the increase in market discipline should therefore come from shareholders, bondholders, and large depositors.

A specific convertible contingent claim (CoCo), which has been discussed by, amongst others, Calomiris and Herring (2013), could further strengthen the scrutiny by the market, especially by shareholders. This CoCo has three characteristics to ensure that banks take preemptive action to increase their equity before the conversion of the CoCo takes place: 1) the CoCo amount issued must be large relative to total equity, 2) conversion into equity must take place based on a market-based value of leverage when the equity to assets ratio is still high, and 3) common shares must be significantly diluted when conversion takes place. Because converting the CoCo would inflict such high costs on common shareholders, they will pressure banks to raise equity when the banks' situation deteriorates, and more importantly, to prevent this from happening, they will want to make sure the institution never gets into such a situation in the first place.

In addition to the disciplinary pressure from the market, regulators have a complementary role to play in supervising banks, which was not necessarily properly executed in the run-up to the recent crisis. For example, in order to ensure that costs of failure are inflicted on the providers of bank capital, regulators need to be able to liquidate a bank in an orderly manner if severe problems arise. Furthermore, since banks play a role in a functioning payment system, the provision of credit, and securing people's savings, all of which are critical to a society's financial stability but may be less crucial for the providers of bank capital, it is up to the regulators to make sure banks behave prudently. To a certain extent, this introduces regulatory discretion, for example in terms of setting the level and quality of equity requirements. It is therefore essential that regulators keep in mind their main task of guaranteeing the stability of the financial system, which might pave the way for an independent, informed, well-equipped regulator that can obtain and assess relevant information and take action as deemed necessary (Barth, Caprio, & Levine, 2012, Chapter 8). Finally, regulators need to keep their eyes open for unexpected risks, such as the exposure of regular banks to the shadow banking system or institutions fully operating in the shadows. An interesting development in this regard is the emerging "fintech" industry, that is, innovative financial technology companies that are either sponsored by or affiliated with banks or independent organizations providing banking services.

This combined effort on the part of the market and regulators will significantly limit the risks to financial stability. However, it does not eliminate the ability of bankers to take excessive risks. Here, I distinguish between normal risks, that is, pertaining to the task of providing risky credit to the economy, and excessive risks, where bankers are pursuing excessive profits that are "too good to be true." Moreover, if the buildup of such excessive risks goes unnoticed by the market and regulators, it could very well destabilize the financial system. Notwithstanding the possibility of pursuing such risky activities, it should not automatically mean that a banker needs to take advantage of (or misuse) such opportunities.

In Chapters 2 and 4, I focus on the impact a CEO has on bank performance. The findings of Chapter 2 indicate that certain CEO characteristics are strongly associated with this performance. Moreover, Chapter 4 shows that a bank's performance declines in the first years after a new CEO has taken over, which seems to be caused by a discretionary increase in provisions for bad loans. This evidence suggests the importance of CEOs for bank performance. This is likely to be the tip of the iceberg since CEOs are assumed to exert significant influence on a bank's strategy, activities, and corporate culture, as do other executive board members. It is therefore important to select bankers who realize and personally feel that it is their responsibility to ensure a stable financial system. In cases where bank directors do not value such responsibilities, regulators should step in to prevent imprudent bankers from being able to jeopardize financial stability by not allowing them to work in important positions within the bank.

If the market and regulators exert sufficient effort to ensure the safe operation of banks, including the appointment of prudent bankers, problems are much less likely to occur. However, if such problems do occur, it is important that banks' resilience be enhanced in order to limit the overall harm to society. In addition to ensuring orderly liquidation, as discussed above, banks should hold significantly more equity, and of higher quality. Increasing the level and quality of the unweighted equity to assets ratio decreases the likelihood of a bank's failure, because it provides for a larger cushion to cover unexpected losses. Therefore, a high ratio of unweighted equity to assets (let's say higher than 10%) is required.

In the discussion on raising the levels of equity, it is important to distinguish between the goal of making the financial system safer and the path for reaching this goal. A bank has three possibilities for increasing its equity to assets ratio: 1) raise equity in the financial markets, 2) retain earnings, and 3) shrink the balance sheet. Although banks were able to raise money in the market during and after the crisis, they have remained reluctant to do so because they worry that the market interprets this as a sign of weakness. Since closing the gap with retained earnings takes such a long time, banks have also shrunk their balance sheet. This has led to less generous credit provisioning, which has potentially hampered a swift economic recovery, especially in Europe. However, the positive benefits of a more robust financial system in the long run outweigh the negative consequence of credit contraction in the short run.

In the years since the end of the crisis, there have been improvements in all three of these dimensions. In the U.S. and Europe, regulatory authorities have been set up to liquidate banks in an orderly manner. Moreover, in Europe some banks were liquidated according to a new scheme, under which shareholders, bondholders, and large depositors suffered losses. Even though this was painful for these investors, it was a strong signal to the market that investing in banks comes with risks. This is likely to strengthen the disciplinary pressure of the market. Furthermore, since convertible contingent (CoCo) claims qualify as Total Loss Absorbing Capacity (TLAC) introduced by the Financial Stability Board, there have been multiple CoCo claims issued. These claims might help in the orderly liquidation of troubled financial institutions, because if problems arise, the conversion of debt to equity allows an institution to continue its operations, giving regulators more time. However, these securities come in all kinds of forms, with diverse sets of objectives, which can have unintended negative consequences for financial stability. The main objective of the instrument proposed above (Calomiris & Herring, 2013) – that is, the issuance of equity before an institution becomes troubled – is not the main goal of these instruments per se. Therefore, regulators should restrict the use of CoCos that suffer from these unintended negative consequences. Besides inducing more market discipline by a liquidation scheme, the regulatory regime has been strengthened across many dimensions in the U.S. and Europe. The banking union in Europe, where supervision of the largest banks is now performed by the European Central Bank, and the Dodd–Frank Act in the U.S. have intensified the grip of regulators. However, it is important not to overregulate the market. The ability of regulators to intervene before the crisis was not necessarily too limited, it was simply not properly put to use. It is therefore doubtful, for instance, whether the vastness and complexity of the Dodd–Frank Act in the U.S. will be effective in securing a well-functioning, stable financial system.

On the second dimension, which considers the motivational and behavioral aspects of bankers, there are early signs that banks and regulators are exerting effort. The Dutch Central Bank, for example, performs tests on the psychological and behavioral characteristics of senior bankers and supervisory board members. Although it is difficult to publish this information for privacy reasons, it has been documented that some people in the financial sector did not pass the test and, as a result, had to give up their position or were not appointed in the first place. Despite the difficulty of uncovering policies, common practices, and the culture within banks, there is some indication that banks are becoming more reluctant to hire/promote bankers who are just willing to pursue the most profitable strategies. However, it is too early to judge whether this is a structural change being applied across the banking industry or an exception to the rule.

Finally, there has been a significant increase in the level and quality of equity in both the U.S. and Europe. Unweighted equity to assets ratios have been introduced and banks are even increasing their ratios above regulatory minimum levels, potentially due to competitive pressures or to impress markets.

In sum, I conclude that the stability of the financial system has improved since the financial crisis. The oversight of banks by the market and regulators has increased. This will curb the possibilities for banks to take on excessive risks. Moreover, even when banks are presented with opportunities to benefit at the expense of society, there are early signs that regulators and the banks themselves are trying to prevent this from happening by taking into account the integrity and motivation of bankers. If these two lines of defense prove to be ineffective, a significant, but as of yet insufficient, increase in equity and the possibility to orderly liquidate banks will limit the spread of problems to society.

2 | Why Did U.S. Banks Fail? What Went Wrong at U.S. Banks in the Run-Up to the Financial Crisis?

Co-Author: Kees Cools

Abstract

This chapter analyzes the differences between weak and strong U.S. banks prior to the financial crisis (2002–2006), whereby we have defined strength as the ability to endure the crisis independently. Weak banks either went bankrupt, were acquired due to financial distress, or did not pass the stress test and needed government support. Strong banks, on the other hand, passed the test and repaid the government support as soon as they were allowed to.

A pronounced difference between weak and strong banks was their buy-and-hold stock returns from January 2000 through February 2015. Weak banks outperformed strong ones in the run-up to the crisis by 113% but subsequently lost 94% of their market value in the crisis and did not recover to pre-crisis levels afterwards. Strong banks lost 71% of their market value but their stock price is currently above pre-crisis levels.

We argue that the strength of these banks is ultimately determined by their structure (i.e., formal governance) and the agency (i.e., behavior) of their em-

ployees. We found that the quality of formal governance, as measured by CEO duality (i.e., when the CEO is also Chairman of the Board) and the rights of shareholders versus management, was slightly *lower* at strong banks. However, the CEOs of weak banks had received higher cash bonuses. Moreover, they had a significantly higher incidence of having been raised in a low socioeconomic environment than their counterparts at strong banks. Finally, we document that weak banks were exposed to more funding risk (lower equity and higher debt), market risk (higher loans to assets ratio), and liquidity risk (more short-term debt) than strong banks.

2.1 Introduction

The last financial crisis, the worst since the Great Depression in the 1930s, started in the United States in 2007 and reached Europe soon afterwards. It had far-reaching consequences. Most of the direct costs related to the crisis were incurred rescuing financial institutions. The U.S. treasury spent a total of $614bn to bail out the financial sector (Kiel & Nguyen, 2015) and the Federal Reserve injected $1,200bn of liquidity support into the system (Keoun, 2014).

Although problems at financial institutions (primarily banks) were at the core of the financial crisis, the costs of rescuing these institutions were not the only costs incurred. The broader economy suffered, as well: in the first quarter of 2014, U.S. GDP fell 17% behind its 1950–2007 growth trajectory (Wolf, 2014). Other major problems can also be ascribed to the crisis, such as increased unemployment, loss of pension savings, budget cuts, and higher budget deficit and government debt levels.

In this chapter, we aim to answer the following question: How did strong banks differ from weak banks in the run-up to the financial crisis? In Europe, the distinction between strong and weak banks is fairly easy to make, because there were numerous banks that did not need or receive government support and endured the crisis on their own, while others needed government support or failed. In the U.S., however, it turns out that all of the major surviving U.S. banks received state aid. We therefore used an alternative classification criterion to define strong versus weak banks: a U.S. bank is considered weak if it went bankrupt (e.g., Lehman Brothers), was acquired due to financial distress (e.g., Bear Stearns), or failed to pass the FED's stress test (e.g., Citigroup). Strong banks passed this stress test and were the first ones allowed to repay the support they received (e.g., JPMorgan Chase and Goldman Sachs).

Before focusing on the banks' strength, we will discuss the underlying forces that determine how an organization functions. We look at these institutions from the perspective of the sociological theory of structuration (Giddens, 1979), in which a combination of structure and agency shapes (the workings of) an organization. Structure is perceived as the coagulated activities of actors, which in its turn restrains and supports those actors. Applying this framework to our setting, we argue that the strength of a bank is ultimately determined by a combination of the bank's formal governance (i.e., structure) and the behavior (i.e., agency) of its employees. As a proxy for the formal governance, we consider two factors: the division of power between shareholders and management and CEO duality (when the CEO is also Chairman of the Board). In terms of the behavior of the employees, we focus on two behavioral drivers for the CEO: remuneration and socioeconomic background. Although the CEO is just one employee, s/he is the most powerful one (Hambrick & Mason, 1984) and exerts a significant impact on corporate outcomes (Bertrand & Schoar, 2003; Graham, Harvey, & Puri, 2013). We compare remuneration at weak and strong banks, since it has been put forth as an important contributing factor to the financial crisis (Diamond & Rajan, 2009). In addition, motivated by the upper echelons theory introduced by Hambrick and Mason (1984), we relate the CEOs' socioeconomic backgrounds (measured by the prestige of their fathers' profession) to the strength of banks. We build on recent research by Kish-Gephart and Campbell (2015), who link the class in which a CEO grew up to risk-taking at the firm level. To the best of our knowledge, this is the first study to investigate this topic in relation to the financial crisis. Besides examining the governance and behavioral dimensions, we also compare weak and strong banks in terms of their capital adequacy, assets quality, earnings, liquidity, growth, and size.

We found that the quality of formal governance of weak banks was slightly better than that of strong banks: the CEO and chairman positions were separated more often at weak banks, and their shareholders had more rights versus management than their counterparts at strong banks. On the other hand, we document more pronounced differences in terms of behavioral drivers, such as cash bonuses, typically geared towards the short term: these were over 40% higher for CEOs at weak banks compared to their peers at strong banks, while restricted stocks and options, which are geared towards the long term, were 5% higher at strong banks. Furthermore, weak banks' CEOs were raised in lower-class environments significantly more often than their counterparts at strong banks.

The financial characteristics show a clearer difference: weak banks were more risky than strong banks, as reflected by their higher leverage, larger fraction of short-term debt, and higher exposure to market risk, with up to 49% of their assets comprised of loans – 10 percentage points higher than for strong banks. This did not, however, translate into higher earnings: the strong banks were approximately 20% more profitable overall.

Finally, we compare the buy-and-hold stock returns as of 2000 for both bank types to assess how the market perceived the quality of these banks. The returns for weak banks were 113% higher prior to the crisis than for strong ones. During the crisis, weak and strong banks lost 94% and 71% of their market value, respectively, after which only the strong banks recovered to pre-crisis levels. Even though weak banks were less profitable overall before the crisis, they strongly outperformed strong banks in terms of stock returns, which might have been driven by the higher riskiness that led to the collapse during the crisis.

This chapter makes three contributions. First, we devise a comprehensive model to identify the forces that determine the strength of a bank. Although there has been research that focused on the financial characteristics of banks (Cole & White, 2012), the role of governance as measured by the shareholder friendliness of boards and institutional ownership (Beltratti & Stulz, 2012; Erkens, Hung, & Matos, 2012), the incentive alignment of CEOs and shareholders (Fahlenbrach & Stulz, 2011), and the role of risk management (Aebi, Sabato, & Schmid, 2012; Ellul & Yerramilli, 2013), we are not aware of any research considering governance, behavioral, and financial characteristics in a coherent framework. Building on the sociological theory of structuration developed by Giddens (1979), we argue that the strength of a bank to independently withstand the financial crisis was a combination of corporate governance (structure) and drivers of behavior (agency).

Second, we contribute to the literature that deals with measuring the performance of banks during the financial crisis. In order to measure crisis performance, we formalize the methodology of Calomiris and Herring (2013), who categorized banks according to their ability to withstand the crisis independently.[1] Related research comparing banks that went bankrupt in the crisis to surviving banks (e.g., Cole & White, 2012; Fahlenbrach, Prilmeier, & Stulz, 2012) has treated all surviving banks, that is, banks needing government support to withstand the crisis and those that survived the crisis independently, as if they performed equally well. This contrasts with our categorization, where banks that required government support are taken together with banks that went bankrupt, and are compared to banks that survived the crisis independently. This provides for a cleaner reflection of the bank's financial crisis performance than the crude distinction

[1] Although the criterion to define weak and strong banks is in line with the one used by Calomiris and Herring (2013), they applied this distinction to explore whether their Convertible Contingent debt instrument (CoCo) would have worked to address the Too-Big-To-Fail problem of large financial institutions in the run-up to the crisis. We, on the other hand, want to identify differences between weak and strong banks that might account for them being strong or weak.

between surviving and defaulting banks.

Third, we make a contribution to the relatively novel literature that relates a CEO's socioeconomic background to firm-level outcomes. This chapter is closely related to the setup of Kish-Gephart and Campbell (2015), who show that the class in which a CEO is raised impacts his/her willingness to take company risks. However, this chapter differs in two important ways. First, as opposed to their finding that CEOs raised in an upper-class environment take more risks, we found that these CEOs were significantly more often at the helm of the strong banks, which were characterized by a lower level of riskiness, than of the weak ones. Second, and this might help explain the difference in findings, we focused solely on banks, while they considered all industries in the S&P 1500.

The remainder of the chapter is organized as follows. Section 2.2 discusses the dependent and independent variables. The data is described in Section 2.3, while Section 2.4 discusses the methodology. Results are presented in Section 2.5, and Section 2.6 presents our conclusions.

2.2 Weak and Strong Banks and Their Differences

In Section 2.2.1, we distinguish between weak and strong banks. This will be the dependent variable in our multivariate analyses. Subsequently, we document how these two groups performed on the stock market from 2000 to 2015. Finally, Section 2.2.3 describes the dimensions used to compare the banks, which, moreover, represent our independent variables.

2.2.1 The Strength of U.S. Banks

The objective of this chapter is to study the differences between weak and strong banks. Hence, we need to first make a distinction between them. Strong banks passed the FED's stress test (Supervisory Capital Assessment Program) *and* were part of the group that was first allowed to repay the state support. Weak banks did not pass the test and were only eligible to repay the government later on. Banks that were larger than the smallest stress-tested bank (KeyCorp) and had gone bankrupt (Lehman Brothers, Washington Mutual, and Countrywide Financial) or were acquired due to financial distress (Merrill Lynch, Bear Stearns, Wachovia, and National City Corporation) before the stress test was conducted were added to the group of weak banks. Morgan Stanley was not put into either of the two categories since it cannot be classified as a strong bank, having failed the stress test, or as a weak bank, because it was part of the first group allowed to repay. Table 2.1 provides an overview of the weak and strong banks used in our study, their asset size measured in billions of dollars at the end of 2006, and their SIC type.

Table 2.1. Weak and strong banks with asset size as of December 31, 2006, and SIC type. Strong banks passed the FED's stress test *and* were the first banks allowed to repay their government support. Weak banks did not pass the stress test and were only allowed to repay the state aid later on. Banks that were larger than the smallest stress-tested bank and had already gone bankrupt or were acquired due to distress before the stress test are also classified as weak.

Weak Banks	Assets $bn 2006	SIC Type	Strong Banks	Assets $bn 2006	SIC Type
Citigroup	1,884	Retail	JPMorgan Chase	1,352	Retail
Bank of America	1,460	Retail	Goldman Sachs	838	Investment
Merrill Lynch	841	Investment	U.S. Bancorp	219	Retail
Wachovia	707	Retail	Capital One Financial	150	Retail
Lehman Brothers	504	Investment	American Express	128	Finance Serv.
Wells Fargo	482	Retail	BB&T	121	Retail
Bear Stearns	350	Investment	State Street	107	Retail
Washington Mutual	346	Savings Inst.	Bank of New York Mellon[2]	103	Retail
Countrywide Financial	200	Savings Inst.			
SunTrust Banks	182	Retail			
Regions Financial	143	Retail			
National City	140	Retail			
PNC Financial	102	Retail			
Fifth Third Bancorp	101	Retail			
KeyCorp	92	Retail			
Average	502		Average	377	
Median	346		Median	139	
Total	7,535		Total	3,019	

[2]On July 1, 2007, The Bank of New York and Mellon Financial merged into The Bank of New York Mellon. One share of The Bank of New York converted to 0.9434 shares of The Bank of New York Mellon and one share of Mellon Financial converted to one share of The Bank of New York Mellon (see `https://www.bnymellon.com/us/en/investor-relations/merger-information.jsp`). The market capitalizations for The Bank of New York and Mellon Financial at the time of the merger were equal to $31.5bn and $18.4bn, respectively. Moreover, The Bank of New York was much larger than Mellon Financial in terms of assets: $126bn versus $43bn at the end of the second quarter of 2007. We obtained the data from SNL Financial. The Bank of New York was thus considerably larger than Mellon Financial

Although the sample consists of only 23 banks, they accounted for approximately 70% of U.S. banking market assets on December 31, 2006 (see Appendix A for the definition of the U.S. banking market). Furthermore, according to our specification of the U.S. banking sector, the institutions in Table 2.1 were the 23 largest U.S. banks at the end of 2006, except for Morgan Stanley, which has been excluded due to its ambivalent strength.

Initially, we intended to classify a bank as weak if it went bankrupt, was acquired due to financial distress, or received capital support during the financial crisis.[3] For Europe, that criterion works well, but for the U.S., the 17 largest surviving banks all received state aid through the Troubled Asset Relief Program (TARP).[4] The aforementioned criterion would thus have resulted in all major U.S. banks being classified as weak. A closer look revealed that some banks had indicated they did not need any capital support in the first place. The most likely reason that U.S. Treasury Secretary Henry Paulson urged the major banks to accept the state aid was to calm the money markets and restore confidence in the financial sector. If they refused to accept the aid voluntarily, banks were threatened with being forced to do so by regulators anyway.[5] This resulted in state aid being distributed to the largest surviving U.S. banks: the institutions of Table 2.1 still operating independently (i.e., not defaulted and not acquired) and Morgan Stanley.

To restore confidence in the banking sector and determine the strength of these institutions, the Federal Reserve System conducted a stress test, called the Supervisory Capital Assessment Program (SCAP), the results of which were made public on May 7,

and we therefore used the data for The Bank of New York in our analyses.

[3] In addition to capital support, the FED supported the banking system with liquidity support totaling $1,200bn (Keoun, 2014). Only Capital One Financial, one of our strong banks, did not receive this liquidity support.

[4] Bayazitova and Shivdasani (2011) provide a detailed timeline and description of events related to the $700bn TARP. It was composed of the Capital Purchase Program (CPP), which provided capital to strengthen the banks' balance sheets, and the Capital Assistance Program (CAP), which assessed the funding strength of the largest banks by conducting a stress test (Supervisory Capital Assessment Program) and, if funding fell short, requiring banks to raise equity. Moreover, Calomiris and Khan (2015) provide an evaluation of the social costs and benefits of TARP, such as costs related to corruption in the administration of the program and benefits of improving the health of financial institutions.

[5] See `http://www.judicialwatch.org/files/documents/2009/Treasury-CEO-TalkingPoints.pdf` for the talking points Henry Paulson used in his meeting with the nine most important U.S. banks.

2009 (Board of Governors of the Federal Reserve System, 2009). A total of 19 institutions were tested, comprising the 17 mentioned earlier plus MetLife and General Motors Acceptance Corporation. We eliminated the latter two institutions from our study because they are not banks but rather an insurance company and the financial arm of a car company, respectively. The banks were tested over a two-year time horizon under two scenarios: the baseline scenario (the consensus forecast) and a more adverse scenario, where the loss rate on total loans was equal to 9.1% (higher than any two-year loss rate in the 1920–2008 period). Furthermore, the expected profits during this two-year period were estimated conservatively. A financial institution passed the test if the Tier 1 common capital ratio and Tier 1 capital ratio remained above 4% and 6%, respectively, in the more adverse scenario.

Eight of the banks passed the test and nine failed. Moreover, these eight were the first of the 17 stress-tested banks that were eligible to repay the TARP funds, and they did so soon after the stress test. Morgan Stanley did not pass the test, but it was also allowed to repay its government support as one of the first banks since it had acquired enough capital through common stock share issues shortly after the SCAP results were presented (see Romero, 2011, pp. 13–14). Although TARP funds were listed on the balance sheets of the banks as Tier 1 capital during the test, we are convinced that the eight banks that passed would have done so without the TARP capital anyway. Since TARP support was part of the Tier 1 capital and not the more narrow[6] Tier 1 *common* capital, we only have to assess whether banks passing the test would have had enough Tier 1 capital were they stress tested without the government money. In a document from the Special Inspector General for TARP (Romero, 2011),[7] the following paragraph is found regarding the eight banks that passed the test and Morgan Stanley:

[6]Narrow in the sense that not all Tier 1 capital is Tier 1 common capital, but all Tier 1 common capital is Tier 1 capital.

[7]On `www.sigtarp.gov`, the goal of SIGTARP is summarized as follows: The Office of the Special Inspector General for the Troubled Asset Relief Program (SIGTARP), a sophisticated, white-collar law enforcement agency, was established by Congress in 2008 to prevent fraud, waste, and abuse linked to the $700bn TARP.

> For SCAP institutions repaying in June 2009, TARP repayment lowered an institution's Tier 1 capital ratio by an average of 114 basis points[8] (from 11.06% to 9.91%) as projected by FRB through 2010. However, FRB also projected that Tier 1 common ratios increased by an average of 133 basis points (from 6.57% to 7.90%) due to the new common stock each repaying institution was required to issue.[9] (p. 15)

Consequently, we conclude that the average projected Tier 1 capital ratio at the end of 2010 without TARP funds and without the additional common stock issuance would have been equal to 11.06% - 1.14% - 1.33% = 8.58% for the nine institutions repaying in June, which is considerably above the minimum requirement of 6%. It therefore seems warranted to classify the eight banks that passed and were allowed to repay first as strong. The banks that failed the test, went bankrupt, or were acquired due to distress comprise the group of weak banks. Although this distinction between weak and strong banks has, to the best of our knowledge, not been used before, Calomiris and Herring (2013) used a related criterion for separating banks requiring government support during the crisis from banks able to withstand the crisis independently.[10] In the remainder of the chapter, we will compare the characteristics of the weak and strong banks.

2.2.2 Market Perspective

We start our comparison between weak and strong banks with their stock returns in the years before, during, and after the financial crisis. To do so, we computed the buy-and-hold stock returns for individual banks and took the unweighted average of the eight strong (thick line) and 15 weak (thin line) banks to construct a strong and a weak bank index. The stock price data were obtained from Bloomberg. The development of these

[8]A basis point represents 1/100 of a percent. For example, an increase from 5.25% to 5.50% would be an increase of 25 basis points.

[9]The average change in FRB's projected Tier 1 capital and Tier 1 common ratios for institutions that repaid in June 2009 was determined by calculating a simple average of the institutions' projected ratios.

[10]Unfortunately, we cannot be more specific as Calomiris and Herring (2013) do not explicate how they distinguished banks that did not require government intervention (see Figure 3) from banks that did require such intervention (see Figure 4).

indices is presented in Figure 2.1.[11]

Stock Price Index of Weak and Strong U.S. Banks 2000–2015

(dividends reinvested)

3-1-2000 = 100

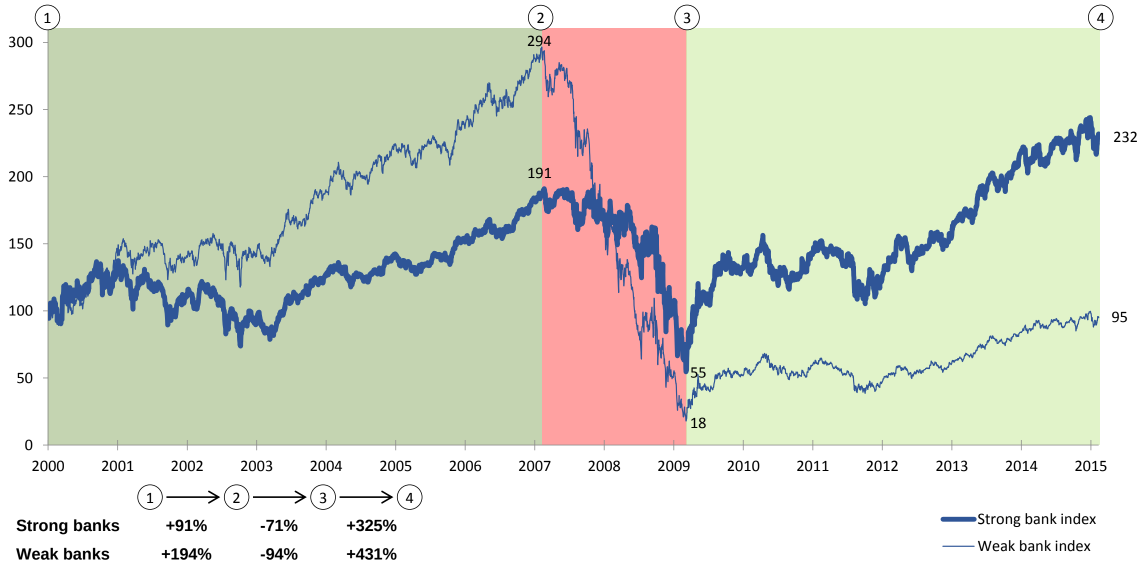

Figure 2.1. Stock prices, adjusted for reinvestment of dividends and stock splits, for the unweighted index of weak and strong U.S. banks from 2000 to 2015.

Considering the trajectory of the buy-and-hold stock performance, we can divide the period from January 2000 to February 2015 into three time periods: *rise*, *fall*, and *recovery*. In the *rise* period (ending at February 2007), the stock returns of weak banks were equal to 194%, while the price of strong banks increased by "only" 91%. This translates into a compounded average growth rate of 14.9% for weak banks and 9.1% for strong ones, which is significant at the 5% level when we employ a t-test to compare the means of the two groups.

Calomiris and Haber (2014, pp. 275–277) discuss possible reasons for the heterogeneity in pre-crisis performance between weak and strong banks. They argue that weak banks purposefully pursued more risky strategies than strong banks.[12] In order to keep up with strong banks, weak banks were investing in high-risk assets while maintaining

[11] See Appendix B for the method used to construct these indices.

[12] This is consistent with the findings of Ellul and Yerramilli (2013), who document that banks with a stronger commitment to risk management, as measured by the ratio of the chief risk officer's compensation to the chief executive officer's compensation, took less risk before the crisis and experienced smaller losses during the crisis.

only a thin layer of equity to cover for unexpected losses. Their strong counterparts, on the other hand, were better positioned to invest in high-quality lower-risk projects and maintained decent levels of equity. In addition to elevated levels of risk, weak banks might have inflated their returns by increasing the size of government subsidies, such as the explicit deposit insurance and the implicit too-big-to-fail guarantee (Calomiris & Haber, 2014, p. 258). The largest banks with the lowest levels of equity, that is, the ones with the largest government subsidies, experienced less scrutiny from depositors and other creditors, which led to low borrowing costs and even lower levels of equity. Considering that, in the run-up to the crisis, our median weak bank was two times larger and held less equity than the median strong bank, this might also have been a contributing factor to the pre-crisis outperformance of weak banks.

In the next two years, 94% of the weak banks' market value evaporates, whereas the strong banks lose 71%. Hence, the loss in market value is in line with our classification of weak versus strong banks. In the *recovery* period, it turns out that strong banks were able to recover this loss in market value, to the extent that their stock prices in February 2015 were higher than before the start of the crisis. The weak banks recovered, as well, but never come close to pre-crisis levels. In sum, weak banks significantly outperformed strong banks in the years before the crisis. This reversed during the crisis when weak banks lost almost all their market value. Furthermore, they were unable to recover to pre-crisis levels in the six years after the crisis, whereas strong banks did recover.

2.2.3 Determinants of Strong Versus Weak Banks

In Section 2.2.1, we categorized banks as being either weak or strong. In this section, we will focus on the underlying dynamics propelling organizational outcomes, which in our case define the strength of the banks in question. To identify these dynamics, we use a definition of institutions from the sociology literature: "Institutions are comprised of regulative, normative and cultural-cognitive elements that, together with associated activities and resources, provide stability and meaning to social life" (Scott, 2008, p. 48).

This definition applies to institutions in general, ranging from divisions within a corporation to non-governmental organizations and even supranational organizations. We employ it in the context of a corporate organization – more specifically, a bank. The first part of the definition focuses on the structure of organizations. This structure comprises "legal, moral and cultural boundaries" (Scott, 2008, p. 50) that are meant to guide the activities of the actors operating in an institution. Conversely, an organization might not only limit actors, but also provide support with its resources. Furthermore, in addition to restrictions and support, the actors' own volition has an impact on organizational outcomes. This contrast between agents, on the one hand, and structure, on the other, has been a central debate in sociology for over a century and has more recently also found its way to economics (e.g., Lawson, 1994) and management (e.g., Reed, 2005). Giddens (1979) combines these opposing forces in his theory of structuration, in which structure is interpreted as coagulated activities. However, although structure constrains the latitude of actors, they are still able to influence organizational outcomes by determining whether and how they will obey the rules. Conversely, their actions can ultimately lead to adjustments in the rules, mores, and culture.

We will now transpose this view of an organization to the bank setting in order to identify the underlying forces that might have caused these banks to perform strongly or poorly during the crisis. Applying the structure and agency framework, we attempt to measure structure according to the formal governance of the banks. While we are aware that this measure of structure largely ignores moral and cultural components, unfortunately, these are much more challenging to measure and we must therefore discard them.[13] We operationalize the agency dimension as the behavior of employees.[14] This measuring of activities by employees in the multitude of instances in which they engage is a formidable task, so we need to narrow it down. First, we restrict our attention to

[13]See, e.g., Zingales (2015a) in the introductory paper of the special issue of the *Journal of Financial Economics* dedicated to the NBER Conference on the Causes and Consequences of Corporate Culture. Here, corporate culture is not measured separately but is the aggregation of the personal beliefs and values of employees. In our view, such personal belief systems solely influence employee behavior and, consequently, do not pertain to the culture of a firm.

[14]A broader definition of actors would also, for instance, include customers, suppliers, and competitors.

CEOs, since they are the most important actors in an organization (Hambrick & Mason, 1984) and materially influence corporate outcomes (e.g., Bertrand & Schoar, 2003; Graham et al., 2013). Second, we focus on particular dimensions that drive the behavior of CEOs.

The above discussion is graphically summarized in Figure 2.2. Arrow (1) shows the impact of structure and agency on a bank's strength. In addition to the structure and agency factors, there are also external factors that influence that strength, such as the economic growth in the area that a bank operates in.

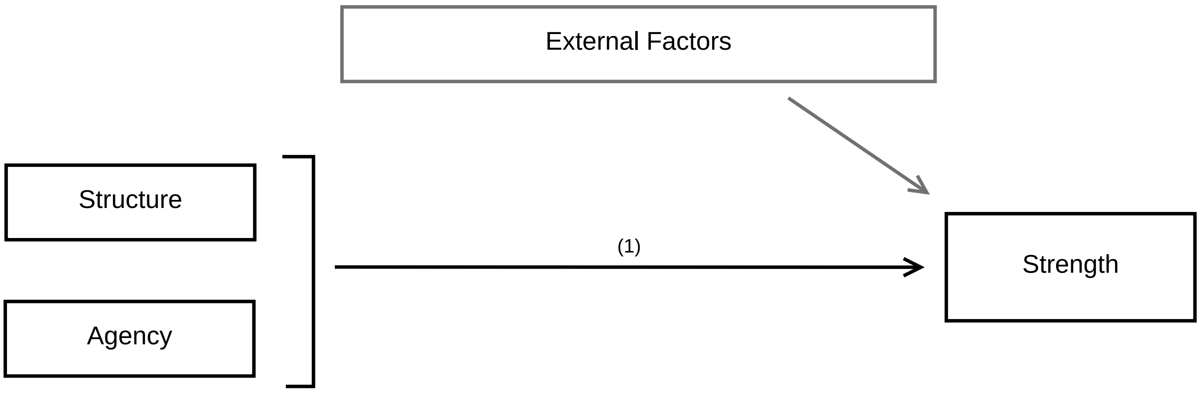

Figure 2.2. Theoretical framework of the firm, I. The strength of a bank is – ultimately – determined by its structure and agency, which is indicated by Arrow (1). Factors that influence a bank's strength, but are not controlled by that bank, are designated as external factors.

In addition to this set-up, we follow the extant banking literature that relates a bank's financial characteristics to performance and survival (e.g., Beltratti & Stulz, 2012; Berger & Bouwman, 2013; Fahlenbrach et al., 2012). This relation is depicted by Arrow (2) in Figure 2.3.

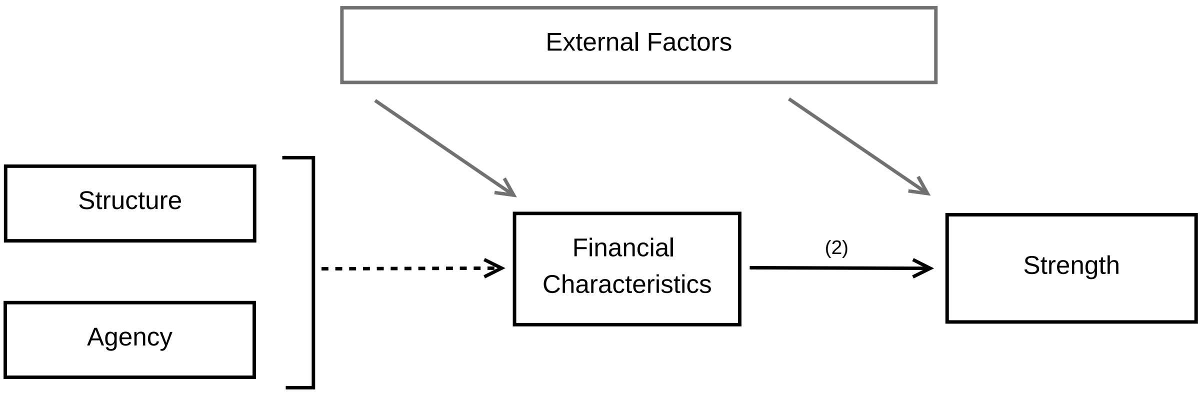

Figure 2.3. Theoretical framework of the firm, II. We relate the strength of banks to their financial characteristics as depicted by Arrow (2). These characteristics are again determined by structure and agency, as shown by the dashed arrow. Factors that influence a bank's strength, but are not controlled by that bank, are designated as external factors.

Since we have argued that structure and agency determine organizational outcomes, they also determine the financial characteristics of banks. As an example, consider the finding of Berger and Bouwman (2013), who have shown a positive relationship between the fraction of the balance sheet funded with equity and the probability of survival during crisis times (Arrow [2]). Banks characterized by a cautious culture and/or a more prudent CEO are likely to be more reluctant to choose high-leverage (dashed line), which increases their odds of survival.

Structure

We use proxies to measure the formal governance of a bank's structure. We were forced by the availability of data to focus solely on these rule-based boundaries of firms and ignore the moral and cultural restrictions. Good corporate governance practice implies that power is not solely concentrated in the company's management, but also shared with shareholders. The rights of shareholders should be balanced with the decision rights of management, and a good system of corporate governance should prevent "managerial capitalism," given that management has certain fiduciary duties towards its shareholders as residual claimants of the firm (Shleifer & Vishny, 1997).

Weak banks were unable to withstand the financial crisis on their own, which was, moreover, accompanied by a decline in stock prices of 94% (see Figure 2.1). Therefore, ex post, their shareholders must have been unhappy with outcomes, which could have been attributed to inadequate formal governance at these banks. However, this is not in line with Beltratti and Stulz (2012), Erkens et al. (2012), and Fahlenbrach and Stulz (2011), who found a negative relationship between quality of governance (shareholder-friendliness of boards, alignment of CEO and shareholders, level of institutional ownership) and performance during the crisis. The negative relationship between quality of governance and performance during the crisis does not extend to the risk governance of banks. Ellul and Yerramilli (2013) documented a positive relationship between the strength and independence of the risk management function within a bank, on the one hand, and stock returns and operating performance during the crisis, on the other. In sum, although some facets of corporate governance seem not to have been in the long-term interests of shareholders, centrality of risk management was key to the crisis performance of banks.

To assess the impact of governance on bank strength, we focus on two dimensions: shareholder rights vis-à-vis management power and CEO duality. We employ the *Governance Index* of Gompers, Ishii, and Metrick (2003) to measure shareholder rights. The index consists of 24 corporate governance provisions related to shareholder rights, with each restriction regarding these rights associated with an increase of one index point. Hence, a high score reflects limited rights for shareholders and, thus, extensive rights for management. We compare the *Governance Index* of weak and strong banks. Since Beltratti and Stulz (2012) and Erkens et al. (2012) found a negative relationship between board independence and stock performance during the crisis, we likewise expect to find that according to our measure, weak banks, with their strongly underperforming stock returns during the crisis (see Section 2.2.2), were better governed than strong banks.

In addition, we consider the impact of differences in *CEO Duality* on a bank's strength. The argument against a combined role for CEO and chairman is motivated by agency theory, since it concentrates executive and non-executive power in a single person and implies less internal monitoring of the CEO. Consequently, the trend in the U.S. is a decrease in the practice of combining these roles: from more than 80% in the early 1990s to just over 50% in 2010 (Yang & Zhao, 2014). Despite this trend and the theoretical arguments for separating these two roles, a meta-analysis of 48 studies by Krause, Semadeni, and Cannella (2014) documents no positive relationship between separating these roles and firm performance. Hence, a priori, we do not expect a clear difference between weak and strong banks in this dimension.

Agency

The second driver of organizational outcomes is the agency of employees. Although it would have been highly informative to have gained insight into the behavior of all of the banks' executives (and even better all employees), we focus here on the behavioral drivers of the CEOs, since they hold the most powerful position within an organization (Hambrick & Mason, 1984) and strongly influence corporate outcomes (Bertrand & Schoar, 2003; Graham et al., 2013). Furthermore, the availability of data impedes a broader scope. Since the drivers of CEO behavior are myriad, we chose to focus our analysis on the following two: executive remuneration and socioeconomic background. We selected remuneration because it is perceived to have been an important cause of the financial crisis (Diamond & Rajan, 2009), and we want to establish whether our results are in line with earlier findings relating remuneration practices to the crisis. While the topic of remuneration may have already been well researched, we are, to the best of our knowledge, the first to research the impact of a CEO's socioeconomic background on bank performance during the financial crisis. The recent interest in the management literature regarding the explanatory power of this variable for firm-level outcomes (Kish-Gephart & Campbell, 2015) motivates us to investigate its relevance in explaining bank strength.

Remuneration. Remuneration packages for CEOs are meant to financially and strategically align CEOs with the firm's shareholders and thereby solve the underlying principal-agent problem.[15] In contrast to this theoretical motivation, Bebchuk and Fried (2004) argue that the maximum level of compensation is only constrained by public outrage: that is, bonuses are of no use in motivating CEOs but are instead used to extract rents, which ultimately harms the long-term interests of a firm and its shareholders.

Compensation has also often been raised as one of the main causes of the financial crisis. For instance, Kirkpatrick states that the remuneration before and during the financial crisis was in some cases not in line with "the strategy and risk appetite of the company and its longer term interests" (2009, p. 1). Furthermore, Diamond and Rajan (2009) indicate that remuneration tended to be based on short-term risk-adjusted performance, which stimulated bank employees to search for excessive returns that were not recognized by the financial system as being risky. In hindsight, the high returns should have been interpreted as the compensation for the default risk of the underlying mortgage contracts. Despite these conjectures, Fahlenbrach and Stulz (2011) show that banks with more option compensation or a larger fraction of cash bonus relative to a guaranteed salary did not perform worse during the crisis. This poses a challenge to the notion of executive compensation being a major cause of the crisis.

An alternative explanation of compensation not being positively related to crisis performance is the CEOs' large cashing-out from 2000 to 2008, which diminished the effectiveness of incentive-based compensation. This practice was significantly more prevalent at the fourteen largest U.S. financial institutions receiving government aid than at the banks that survived the crisis independently (Bhagat & Bolton, 2014). Insofar as the high cashing-out was preceded by large remuneration and banks receiving government support performed poorly during the crisis, the performance during the crisis is likely to have been negatively related to pre-crisis remuneration. This relationship is possibly mediated by the higher pre-crisis riskiness of weak crisis performers (Fahlenbrach et al., 2012). Alternatively, a non-causal explanation for the association between compensa-

[15] See Murphy (1999) for a review of the literature that considers executive compensation to be the solution to the principal-agent problem of shareholders vis-à-vis CEOs.

tion and riskiness is formulated by Cheng, Hong, and Scheinkman (2015), who provide evidence that riskier firms need to convince risk-averse CEOs to supply their labor to compensate for the additional riskiness. Overall, the evidence suggests a negative relationship between compensation and crisis performance.

Remuneration of CEOs comprises three main categories: *Fixed Salary*, *Cash Bonus*, and *Delayed Bonus*.[16] Based on the evidence presented above, we expect a higher *Cash Bonus* (typically associated with short-term incentives) and *Delayed Bonus* for weak banks than for strong banks. Moreover, given that *Fixed Salary* only comprises a small fraction of total compensation, we do not expect a difference between weak and strong banks. Furthermore, similar to Fahlenbrach and Stulz (2011), we compare the *Cash Bonus* to *Fixed Salary* for weak and strong banks to measure the relative importance of short-term incentives. An alternative way to measure this relative importance is given by the proportion of *Cash Bonus* to *Delayed Bonus*. Moreover, the use of these ratios alleviates the concern that differences in the magnitude of remuneration packages are driven by size differences among the banks.[17] Since we expect both a higher *Cash Bonus* and *Delayed Bonus* at weak banks, the former ratio is expected to be higher for weak banks, while this is unclear for the latter ratio.

CEO's Socioeconomic Background. There is a diverse and growing literature that deals with the impact of family background on career success, personal characteristics, and firm-level outcomes. When studying intergenerational mobility, an individual's class of origin (i.e., family background), as measured in economics by paternal or household income (Solon, 2002) and in sociology by the father's type of employment (Erikson & Goldthorpe, 2002), is related to his/her class of destination. Although there are cross-country differences (Solon, 2002), the general conclusion is that there is a significant positive correlation between the class of origin and class of destination. In the finance literature, Mullins and Schoar (2016) investigated the family backgrounds of different types

[16] This category comprises restricted stock, stock options, and pension income.

[17] Gabaix and Landier (2008) document a positive relationship between company size and the magnitude of the remuneration package.

of CEOs in 22 emerging markets. They found that founder CEOs of family firms and professional[18] CEOs of non-family firms are more likely to be from lower socioeconomic classes than CEOs related to the founder or current shareholders and professional CEOs of *family* firms. Therefore, they suggest that, in emerging economies, founder CEOs of family firms and professional CEOs of non-family firms provide a means of upward mobility in the social hierarchy.

In the above studies, social class features both as a dependent and independent variable. However, class of origin has also been used as an independent variable to explain personal characteristics. For example, individuals from a higher class are associated with better health (Duncan, Ziol-Guest, & Kalil, 2010) and are more ambitious (Bowden & Doughney, 2010) than individuals from a lower-class. However, Martin, Côté, and Woodruff (2016) demonstrate that social class is negatively related to leadership effectiveness. This relationship is mediated by the higher levels of narcissism observed in individuals raised in an upper-class environment.

The final category of research we consider is the literature focusing on the impact of family background on firm-level outcomes. This literature fills a gap identified by Hambrick and Mason: "There has been almost no attempt in the organizational literature to relate socioeconomic background to organizational strategy or performance" (1984, p. 201). To the best of our knowledge, the Kish-Gephart and Campbell (2015) study is the only one in this area. In it, the authors hypothesize that people from the lower- and upper-classes are more risk-seeking, which subsequently translates into higher risk-taking at the firm level. They argue that the early-life experience of having "nothing to lose" (lower-class) or having a safety net (upper-class) determines prospective attitudes towards risk. This contrasts with people raised in the middle-class, in an environment where parents were concerned with the avoidance of risk in order to keep their job. Their empirical analysis convincingly shows that CEOs from the upper-class engage in

[18] "Professional" meaning an outside manager who is neither the founder nor related to the founder's or shareholders' family/families.

the most risk-taking compared to CEOs from the lower- and middle-classes.

Therefore, combining the results of a negative relationship between pre-crisis bank risk and crisis performance (Fahlenbrach et al., 2012) with the poor stock returns of our weak banks during the crisis (see Section 2.2.2), we expect more upper-class CEOs – associated with higher risk-taking according to Kish-Gephart and Campbell (2015) – at weak banks than at strong banks. The opposite reasoning applies to middle-class CEOs. Finally, since the relationship between risk-taking and lower-class background is weaker in Kish-Gephart and Campbell (2015), we have no a priori expectations on the distribution of lower-class CEOs among weak and strong banks.

Following Mullins and Schoar (2016) and Kish-Gephart and Campbell (2015), we categorize our CEOs into lower-, middle-, and upper-class categories according to a simplified version of the classification system using paternal professions (see Erikson & Goldthorpe, 2002).

Financial Characteristics

In this section, we introduce the financial characteristics we chose for comparing weak and strong banks. We also predict their expected impact on bank strength (see Figure 2.3). In Section 2.2.1, we argued that weak banks would not have survived the crisis without state support. We therefore regard them as failing banks, in contrast to the strong banks that would have survived the crisis independently. Although our sample size is much smaller, our setup is closely related to that of Cole and White (2012), who compared failing banks to surviving ones in the U.S. after the financial crisis. In selecting our variables, therefore, we largely followed their approach and focused on capital adequacy, assets quality, earnings, liquidity, growth, and size.[19]

[19] This selection covers four of the six constituents of the CAMELS rating. That rating is used by U.S. regulators to determine the viability of banks and is composed of: **C**apital Adequacy, **A**sset Quality, **M**anagement, **E**arnings, **L**iquidity, and **S**ensitivity to the Market.

Capital Adequacy. We measured capital adequacy by *Equity to Assets* and the *Tier 1 Ratio*[20] – Tier 1 capital to risk-weighted assets. The higher these ratios, the larger the bank's cushion to cover unexpected losses and the more likely it is to survive. Berger and Bouwman (2013) have shown that for large banks, this applies mainly during periods of banking crisis. Therefore, we expect higher ratios at strong banks than at weak banks before the crisis. Moreover, in the multivariate analysis, we expect a positive relationship between capital adequacy and the probability of strength for banks.

Additionally, we consider *Debt to Assets*, which together with deposits and equity, covers the liability side of the balance sheet. Hence, the larger the fraction of the balance sheet funded with debt, the smaller the deposit base. Since deposits are a stable and cheap form of funding, and the fraction of deposits is inversely related to the fraction of debt, we expect a larger fraction of debt to assets at weak banks.

Asset Quality. The assets of banks mainly comprise loans and securities. Although mortgage backed securities (MBS) were the direct cause of the financial crisis, several studies have shown a negative relationship between *Loans to Assets* (or positive one for *Securities to Assets*) and bank performance during the crisis (Beltratti & Stulz, 2012; Cole & White, 2012; Fahlenbrach et al., 2012). This is likely because MBS only constituted a small portion of the total securities on the balance sheet, while other securities such as bonds are generally regarded as safe assets (Cole & White, 2012). Therefore, we predict a higher fraction of *Loans to Assets* at weak banks.

Earnings. The profitability of a bank is positively related to its chance of survival, since that is what allows the bank to invest in order to remain competitive or add equity to strengthen its balance sheet. Therefore, in line with results from Berger and Bouwman (2013) and Cole and White (2012), we expect higher profitability for strong than for weak

[20]The Tier 1 capital ratio is the ratio regulators primarily focus on in assessing a bank's capital adequacy.

banks, as measured by *Return on Assets* or *Return on Equity*.

Liquidity. During the financial crisis, liquidity was a major problem for banks (Beltratti & Stulz, 2012; Brunnermeier, 2009; Diamond & Rajan, 2009) and the mechanism through which distress spread throughout the system (Brunnermeier, 2009). This was primarily caused by the banks' dependency on short-term (ST) debt. The need to rollover this debt in the short term makes a bank vulnerable to liquidity shortages, which could ultimately lead to default. In order to quantify this dependency, we use *ST Debt to Assets*, and we expect larger values for weak banks than for strong banks.

Growth. Fahlenbrach et al. (2012) showed that bottom performers during the crisis grew significantly faster before the crisis than top performers. They argue that this *Asset Growth* most likely occurred in risky assets. Kedia and Philippon (2009) provide another interpretation for their finding, which is that weak banks were willing to keep up with the growth of strong banks even though they did not have the same positive NPV projects as strong banks. Hence, we expect that weak banks grew faster before the crisis than strong banks.

Size. The final financial characteristic we consider is the *Assets* size of the bank. Larger firms are – on average – organizationally more complex, bureaucratic, and susceptible to internal agency conflicts, which makes them harder to lead. On the other hand, they might also benefit from economies of scale. Therefore, a priori, we do not expect size differences between weak and strong banks.

2.3 Data

In this section, we present our data. Table 2.2 provides an overview of the data sources and years covered per variable.

Table 2.2. Variables, data sources, and years covered.

Variable	Source	Years
Structure		
Governance Index	IRRC	2002, 2004, 2006
CEO Duality	ExecuComp	2002–2006
Agency		
Remuneration	ExecuComp	2002–2006
Socioeconomic Background	Internet search	2002–2006
Financial Characteristics	Bloomberg	2002–2006
Market Perspective		
Stock Prices	Bloomberg	2000–2015

The first column of Table 2.2 corresponds to the categorizations presented in Section 2.2.3. The data cover the 2002–2006 period for all variables, except for the stock prices, which cover the period from January 2000 to February 2015.

The *Governance Index* was constructed using data from the Investor Responsibility Research Center (Gompers et al., 2003), which are made available on Andrew Metrick's website (see `http://faculty.som.yale.edu/andrewmetrick/data.html`). These data were not updated annually, only at seven points between 1990 and 2006. In this chapter, we use the data for the years 2002, 2004, and 2006.

The *CEO Duality* data were collected from ExecuComp. A score of 1 indicates that the CEO is also the Chairman of the Board, otherwise the score is 0. If a succession occurred during the period under consideration (2000–2006), the *CEO Duality* "score" given was that of the CEO in charge for the longest portion of the year. We thus assume that the CEO in charge for the greater part of the year influences firm performance the most. If the succession took place on June 30 or July 1 – that is, exactly in the middle of the year – the observation was excluded.

Remuneration data were also collected from ExecuComp. *Fixed Salary* and *Cash*

Bonus are individually specified in the database.[21] To compute the *Delayed Bonus*, we deducted the *Fixed Salary* and *Cash Bonus* from *Total Compensation*, for which we used the ExecuComp variable *Total Compensation* (Salary + Bonus + Other Annual + Restricted Stock Grants + LTIP Payouts + All Other + Value of Option Grants). If a succession occurred during the year under study, the compensation of the CEO in charge for the longest portion of the year was used. If the succession took place exactly in the middle of the year, the compensation amounts for the predecessor and successor were averaged.

In order to identify the CEOs' fathers' professions and determine their *Socioeconomic Background*, we conducted an internet search. We also approached organizations that these former CEOs currently work for to obtain additional information. In cases where a succession occurred in the period from 2002 to 2006, we took the professions of the fathers of both CEOs into consideration in our analysis. Finally, *Financial Characteristics* and *Stock Prices* were obtained from Bloomberg.

2.4 Methodology

We analyzed differences between weak and strong banks using both univariate and multivariate analysis.

2.4.1 Univariate Analysis

We compared the averages for weak and strong banks per variable and per year. For instance, the average of the *Governance Index* of weak banks in 2002 is compared to the average of strong banks in 2002. The variables we considered were categorized into

[21] An adjustment was made to the *Cash Bonus* category in 2006. Starting that year, a new variable, *Non-Equity Incentive Plan Compensation*, was reported in the ExecuComp database, which was also part of the *Cash Bonus*. This is confirmed by the summary compensation table of Citigroup's DEF14A SEC filings for 2006, in which the *Cash Bonus* entry has been replaced by this new variable. However, since the *Cash Bonus* variable in ExecuComp is not equal to 0 for all banks in 2006, we added together the *Cash Bonus* and *Non-Equity Incentive Plan Compensation* variables from ExecuComp to form our *Cash Bonus* variable for 2006.

continuous, unordered discrete, and ordered discrete variables, and we applied a specific univariate method for each category.

For the continuous variables, the averages were compared using the student t-test developed by Welch (1947). That test allows sample sizes and variances of the weak and strong banks to be unequal. To compare the unordered discrete variables (e.g., *CEO Duality*) for weak and strong banks, we employed Fisher's exact test (R. A. Fisher, 1935). The test is exact in the sense that the p-value does not rely on the sampling distribution of the test statistic becoming equal to the limiting distribution as the sample size goes to infinity. This is especially relevant considering our small sample size. Finally, we applied the Wilcoxon-Mann-Whitney test (Mann & Whitney, 1947; Wilcoxon, 1945) to compare the ordered discrete variables between weak and strong banks. This nonparametric test assesses whether two samples are drawn from the same or different populations. With regard to a CEO's *Socioeconomic Background*, the test compares whether the weak bank's sample is from the same population as the strong bank's sample, for example.

2.4.2 Multivariate Analysis

In addition to the univariate analysis, we conducted a multivariate analysis to identify differences between weak and strong banks. To do so, we employed a logit model where weak banks are designated as 0 and strong banks as 1. To account for any correlation between observations of the same bank in consecutive years (2002–2006), the error terms were clustered at the bank level (Petersen, 2009).

2.5 Results

The structure of the results section is similar to Section 2.2.3, in that we start with the discussion of the structure and agency variables and their impact on bank strength (see Arrow [1] in Figure 2.2) and then shift our attention to the financial characteristics (see Arrow [2] in Figure 2.3).

2.5.1 Structure

We start by comparing weak and strong banks on the quality of the formal governance as measured by the *Governance Index* from Gompers et al. (2003) and *CEO Duality.* Table 2.3 presents the average *Governance Index* for the weak and strong banks per year (left-hand columns) and the number of weak and strong banks where the roles of CEO and chairman were combined (right-hand columns), with the total number of banks under consideration in that category shown in parentheses.

Table 2.3. Quality of formal governance of weak and strong banks. In the left-hand section of the table, the weak and strong columns contain the *Governance Index* averages for the weak and strong banks per year. The bottom line is the average over the years. In the right-hand section of the table, the # weak and # strong columns contain the number of banks where the roles of CEO and chairman were combined, with the total number of observations in parentheses. The p-values in the left-hand section correspond to the Welch t-test and in the right-hand section to Fisher's exact test (see Section 2.4.1.)

Governance Index	weak	strong	p-value	*CEO Duality*	# weak	# strong	p-value
2002	9.6	9.8	0.880	2002	13 (15)	8 (8)	0.526
				2003	14 (15)	8 (8)	1.000
2004	9.5	9.9	0.730	2004	13 (15)	8 (8)	0.526
				2005	12 (14)[22]	8 (8)	0.515
2006	9.4	9.1	0.772	2006	13 (15)	8 (8)	0.526
average	*9.5*	*9.6*	*0.939*				

* $p < 0.10$, ** $p < 0.05$

The division of power between shareholders and management was measured using the *Governance Index* of Gompers et al. (2003), where a higher score corresponds to more limitations on the rights of shareholders and thus more power for management. In the spirit of Shleifer and Vishny (1997), who state that it is the role of governance to assure a return on investment for shareholders, fewer rights for that group is regarded as constituting poor governance. There is no significant difference between strong and weak banks in any of the years. Moreover, in two of the three years, the shareholders of weak banks had even more rights than the shareholders of strong banks. Hence, our results are in line with the earlier findings of Beltratti and Stulz (2012) and Erkens et

[22] Keycorp was excluded from the sample in 2005 because the CEO stepped down in the middle of the year.

al. (2012), who found a negative relationship between performance during the crisis and the shareholder-friendliness of a board.[23]

The combination of the roles of CEO and chairman is, from a governance perspective, unfavorable, since the CEOs must then supervise themselves in their role of chairman. This concentration of power can hamper effective supervision. Our results suggest that *CEO Duality* is not a differentiating characteristic between weak and strong banks. At strong banks, the roles were combined in all of the years, while they were separated at only two weak banks in all of the years, except for 2003, when only one CEO was not also the chairman. However, none of the differences are statistically significant at the conventional levels. Therefore, consistent with the conclusion of Krause et al. (2014), we found no significant relationship between *CEO Duality* and performance. In sum, with regard to the structural dimension, weak and strong banks did not differ substantially in the years leading up to the financial crisis. In the next section, we turn our attention to the agency dimension.

2.5.2 Agency

We focused on the remuneration and socioeconomic background of CEOs as a proxy for agency.

Remuneration

Table 2.4 contains the average yearly *Fixed Salary*, *Cash Bonus*, *Delayed Bonus*, and *Total Remuneration* for CEOs at the banks studied. Furthermore, in the bottom sections of the table, we document the ratios of *Cash Bonus* to *Fixed Salary* and *Cash Bonus* to *Delayed Bonus*.

[23] The negative relationship between the quality of formal corporate governance and crisis performance that we and previous studies (e.g. Beltratti & Stulz, 2012; Erkens et al., 2012) have documented, might suffer from an endogeneity issue. If, in the run-up to the crisis, weak banks' shareholders did not confide in their management they might have demanded and received more shareholder rights to be better able to control management. Strong banks with their superior strategy might have been able to convince their shareholders without the need to grant additional shareholder rights. This is an alternative, non-causal interpretation of the negative relationship between governance quality and crisis performance.

Table 2.4. CEO remuneration at weak and strong banks. The weak and strong columns contain the averages for the weak and strong banks of the variable listed. The p-value given corresponds to the Welch t-test (see Section 2.4.1).

Fixed Salary (in \$ m)	weak	strong	p-value	*Delayed Bonus* (in \$ m)	weak	strong	p-value
2002	1.0	0.8	0.274	2002	9.1	8.0	0.638
2003	1.0	0.8	0.344	2003	11.3	10.6	0.791
2004	1.0	0.8	0.206	2004	12.4	13.4	0.818
2005	1.0	0.8	0.314	2005	11.5	15.2	0.473
2006	1.1	0.8	0.259	2006	15.3	15.5	0.969
average	*1.0*	*0.8*	*0.272*	*average*	*11.9*	*12.5*	*0.849*
Cash Bonus (in \$ m)	weak	strong	p-value	*Total Remun.* (in \$ m)	weak	strong	p-value
2002	3.4	2.8	0.646	2002	13.5	11.5	0.525
2003	7.2	3.1	0.116	2003	19.5	14.5	0.277
2004	5.2	3.5	0.327	2004	18.7	17.7	0.826
2005	7.1	3.8	0.096*	2005	19.6	19.8	0.974
2006	7.5	8.1	0.862	2006	23.9	24.4	0.938
average	*6.1*	*4.3*	*0.289*	*average*	*19.0*	*17.6*	*0.726*
Cash Bonus / Fixed Salary	weak	strong	p-value	*Cash Bonus / Delayed Bonus*	weak	strong	p-value
2002	5.9	3.8	0.556	2002	0.4	0.4	0.820
2003	10.4	3.5	0.122	2003	0.5	0.3	0.248
2004	7.4	4.0	0.343	2004	0.5	0.5	0.831
2005	10.3	4.3	0.173	2005	0.7	4.0	0.397
2006	10.6	11.8	0.868	2006	0.5	0.6	0.626
average	*8.9*	*5.5*	*0.397*	*average*	*0.5*	*0.4*	*0.704*

* $p < 0.10$, ** $p < 0.05$

Since *Fixed Salary* comprises only a minor part of the overall compensation (approximately 5%), the vast majority of remuneration is variable. Therefore, as drivers of behavior, the *Cash Bonus* and *Delayed Bonus* are likely to be more relevant. On average, over the five years prior to the crisis, weak banks paid 42% more in cash bonuses than strong banks. Furthermore, in 2005, this difference is even statistically significant at the 10% level.[24] The larger *Cash Bonus* for weak banks than for strong banks is in line with our expectation. Meanwhile, the *Delayed Bonus* represents the largest share of total remuneration, and it is higher at strong banks than at weak banks both in the last three sample years and when the average is taken over the five years. This result

[24] Goldman Sachs paid a *Cash Bonus* of \$27.2m in 2006, which largely drives the rise for strong banks from 2005 to 2006.

is different from our expectation and indicates that remuneration at strong banks was more geared towards the long term than it was at weak banks.

In the lowest two sections of the table, we compare the ratios of *Cash Bonus* to *Fixed Salary* and *Cash Bonus* to *Delayed Bonus*. This presents two advantages over the comparison of the absolute numbers. First, the use of ratios alleviates the concern that the differences in the sizes of the remuneration packages were caused by differences in the sizes of the banks.[25] Second, it provides a way of measuring the short-term incentives (*Cash Bonus*) relative to unconditional remuneration (*Fixed Salary*) and long-term incentives (*Delayed Bonus*). The *Cash Bonus* to *Fixed Salary* variable averaged over five years is more than 60% higher at weak banks than at strong banks.[26] This difference is largely driven by two outliers, Bear Stearns and Merrill Lynch, where the *Cash Bonus* was 58 times and 16 times larger, respectively, than the *Fixed Salary*. Although the difference is less pronounced, the ratio of *Cash Bonus* to *Delayed Bonus* is approximately 12% larger at weak banks than at strong banks.[27]

Weak banks paid higher *Cash Bonuses* than strong banks, both in absolute and relative terms. Moreover, strong banks granted more bonuses geared towards the long term. Therefore, relative to the CEOs of strong banks, the CEOs of weak banks were more incentivized to focus on short-term gains, rather than on the long-term well-being of the bank.[28]

[25]The median weak bank is almost 2.5 times larger than the median strong bank (see Table 2.1).

[26]We excluded the CEO of Capital One (strong bank) in this analysis because the *Fixed Salary* and *Cash Bonus* are both equal to 0 in all the years.

[27]The high value for strong banks in 2005 is driven by The Bank of New York Mellon, with a ratio of *Cash Bonus* to *Delayed Bonus* of 30. This is not reflected in the average over the five years, because in computing it, we first averaged over the years and then over the banks.

[28]The difference in riskiness between weak and strong banks might also account for the differences in remuneration. Imagine the situation where a risk-averse CEO has to choose between leading a strong or a weak bank. When the CEO is aware of the weak bank's higher riskiness, the risk-averse CEO is only willing to work for this bank, and forgoing the possibility to work for the less risky strong bank, if he is financially compensated for this additional risk. This would be an alternative explanation for the higher *Cash Bonus* at weak banks. Moreover, the lower *Delayed Bonus* at weak banks is consistent with this explanation. For weak banks, the *Delayed Bonus* is a relatively costly way to compensate their risk-averse CEOs, since they substantially discount the future cash flows stemming from the *Delayed Bonus* to incorporate the banks' higher riskiness. Therefore weak banks prefer to compensate their CEOs in cash.

CEO's Socioeconomic Background

In this section, we shift our attention to the early stages of a CEO's life. This analysis contributes to the relatively novel literature that relates the socioeconomic background of CEOs to their decisions at the company level (Kish-Gephart & Campbell, 2015). In our approach, we measure a CEO's class background according to the status of his father's profession, which we divide into lower-, middle-, and upper-classes by applying a simplified version of the categorization identified by Erikson and Goldthorpe (2002). Tables 2.5 and 2.6 list the CEOs, fathers' professions, and classes of the paternal professions for the weak and strong banks, respectively.

Table 2.5. The classification of the CEOs' fathers' professions – weak banks. Professions of the fathers of the CEOs at weak banks in the 2002–2006 period and their corresponding class: 0 = lower-class; 1 = middle-class; and 2 = upper-class.

Weak Banks	**CEO**	**Father's Profession**	**Class**
Citigroup	Charles Prince III	Plasterer	0
	Sanford I. Weill	Dress manufacturer	0
Bank of America	Kenneth D. Lewis	Lumberyard poultry plant, army	0
Merrill Lynch	E. Stanley O'Neal	Assembly line	0
	David H. Komansky	Post office job	0
Wachovia	G. Kennedy Thompson	Manager at textile mill	1
Lehman Brothers	Richard S. Fuld Jr.	Army officer	1
Wells Fargo	Richard M. Kovacevich	Sawmill worker	0
Bear Stearns	James E. Cayne	Patent attorney	2
Washington Mutual	Kerry K. Killinger	Musician and musical teacher	0
Countrywide	Angelo R. Mozilo	Butcher	0
Suntrust	L. Phillip Humann	Job at oil-and-gas shipper	0[29]
National City	David A. Daberko		
Regions Financial	C. Dowd Ritter		
	Jackson W. Moore	Medical doctor	2
	Carl E. Jones, Jr.		
PNC Financial	James E. Rohr	Small restaurant owner	0[30]
Fifth Third Bancorp	George A. Schaefer, Jr.		
Keycorp	Henry L. Meyer, III		

Table 2.6. The classification of the CEOs' fathers' professions – strong banks. Professions of the fathers of the CEOs at strong banks in the 2002–2006 period and their corresponding class: 0 = lower-class; 1 = middle-class; and 2 = upper-class.

Strong Banks	**CEO**	**Father's Profession**	**Class**
JPMorgan Chase	James Dimon	Stockbroker, exec. vice pres. AmEx	2
	William B. Harrison Jr.	Peoples Bank, real estate developm.	1
Goldman Sachs	Lloyd C. Blankfein	Bakery truck driver, clerk	0
	Henry M. Paulson Jr.	Wholesale jeweler	1
U.S. Bancorp	Richard K. Davis		
	Jerry A. Grundhofer	Bartender	0
Capital One Financial	Richard D. Fairbank	Physics professor	2
American Express	Kenneth I. Chenault	Dentist	2
BB&T	John A. Allison IV		
State Street	Ronald E. Logue		
	David A. Spina		
Bank of NY Mellon	Thomas A. Renyi	Medical doctor	2

These tables show that the CEOs of the weak banks more frequently came from the lower-class than those of the strong banks: 10 of the 14 weak banks' CEOs came from a lower-class background compared to two of the eight CEOs of the strong banks. Conversely, half of the CEOs of the strong banks were from the upper-class compared to only two at the weak banks. The remaining two CEOs in both groups were raised in a middle-class environment.

To determine whether this difference in the CEOs' socioeconomic background was also statistically significant, we employed the Wilcoxon-Mann-Whitney test (see Section 2.4.1). This test determines the likelihood that the weak and strong banks' samples were drawn from the same population, assuming an equal probability of CEOs being raised in one of the three classes. This test (with a p-value equal to 0.034) rejected the null hy-

[29] We have not been able to find more specific information regarding the nature of the job. It is therefore difficult to judge whether it was a higher or lower ranking job at the oil-and-gas company. Even if the class of the job were to be changed from 0 to 1, the class difference between the weak and strong banks' CEOs would remain significant, with a p-value of 0.054.

[30] The profession is classified as 0 because his father passed away when he was 10 and his mother was not able to keep the restaurant. Under normal circumstances, a small restaurant owner would have been classified as 1.

pothesis that the samples were drawn from the same population. We therefore conclude that the CEOs of weak banks were raised in a lower-class environment significantly more often than their counterparts at strong banks. This is not in line with our expectation, since we expected to find more upper-class CEOs at the riskier weak banks, based on the results of Kish-Gephart and Campbell (2015). One possible explanation for this could be the difference in samples: Kish-Gephart and Campbell used S&P 1500 companies, whereas we focused exclusively on the largest U.S. banks.

At this point we want to investigate the possibility that strong banks, with their upper-class CEOs, were favored by regulators in the stress test discussed in Section 2.2, which potentially distorts our classification of the banks. Before we discuss possible ways in which this might have occurred, we assess the trustworthiness of the stress test. According to Acharya, Pedersen, Philippon, and Richardson (2017) the stress test was "generally considered to be a credible test" (p. 17), which is the first indication that regulators were not favoring certain banks. However, other concerns remain. The stress test assessed the capital adequacy of banks in an adverse economic scenario (see Section 2.2). Two critiques that have often been voiced regarding capital adequacy measures of banks is the use of book values of equity instead of market values and risk weighted assets instead of total assets (Acharya, Engle, & Pierret, 2014; Calomiris & Herring, 2013). These critiques also pertain to the SCAP. Therefore, we resort to an alternative measure of bank strength, called SRISK, which has been introduced by Brownlees and Engle (2017) and Acharya, Engle, and Richardson (2012), to compute the expected equity shortfall per bank when a systemic crisis hits. In Table 2.7 we present this shortfall divided by total assets on December 31, 2008,[31] which we obtain from the Volatility Institute at the NYU Stern School of Business,[32] for the banks in our sample that were still active at that time. These shortfalls are computed when the market declines with 40% and the minimum required equity to assets ratio for banks equals 4%.

[31] This is the same date as the starting point used in the SCAP.
[32] See `http://vlab.stern.nyu.edu/welcome/risk/`.

Table 2.7. The expected equity shortfall of weak and strong banks, using SRISK (Acharya et al., 2012; Brownlees & Engle, 2017), relative to their assets as of December 31, 2008. The equity shortfall is computed assuming that the market declines with 40% and banks are required to have at least 4% of equity to assets. Banks are ordered with respect to their relative expected equity shortfall.

Institution	Weak / Strong	Equity Shortfall to Assets
Citigroup	Weak	3.22%
Wachovia	Weak	3.15%
Merrill Lynch	Weak	3.04%
National City	Weak	2.03%
Goldman Sachs	Strong	1.90%
Bank of America	Weak	1.86%
KeyCorp	Weak	1.65%
JPMorgan Chase	Strong	1.61%
Regions Financial	Weak	1.30%
Fifth Third Bancorp	Weak	1.08%
SunTrust Banks	Weak	0.38%
PNC Financial	Weak	0.08%
Capital One Financial	Strong	0.00%
Wells Fargo	Weak	-0.94%
State Street	Strong	-1.64%
BB&T	Strong	-2.31%
Bank of New York Mellon	Strong	-3.51%
American Express	Strong	-3.75%
U.S. Bancorp	Strong	-5.51%

Subsequently applying the Wilcoxon-Mann-Whitney test (see Section 2.4.1), we find that there is a significant difference in relative expected equity shortfall between weak and strong banks. Moreover, the probability that the relative shortfall for weak banks is larger than for strong banks equals 0.852. In sum, SRISK, a methodology based on market values of equity and total assets, is in line with the SCAP results, and corroborates our classification of weak and strong banks.

Even though this substantially reduces concerns regarding the subjectivity of regulators responsible for the stress test, the myriad of interlinkages between the financial sector and the government, as described in Calomiris and Haber (2014), could also have played a role in this particular situation. We make two remarks to counter this argument. First, Calomiris and Haber typically focus on general coalitions between the government and the financial sector, in contrast to specific coalitions between the government and individual institutions, which is our worry here. Second, if strong banks were better able to influence the regulators, we would expect that their CEOs would have been part of the financial sector for a longer time than CEOs of weak banks. Comparing the average time weak and strong banks' CEOs worked in the financial sector, at the time of the stress test, we found the opposite, that is, weak bank CEOs were around for 33 years while strong bank CEOs worked in the industry for 27 years. In sum, we have no indication that strong banks were treated favorably in the stress test and even if CEOs would have been able to influence the test, weak banks' CEOs, with their longer careers in the financial sector, would have been better positioned than their counterparts at strong banks.

Therefore, we now wonder what could be reasons that CEOs of the largest U.S. banks that went bankrupt or needed government support had a lower-class background significantly more often than those at the banks that survived the crisis independently. Even though the lower-class CEOs faced additional challenges in their youth, compared to upper-class CEOs (Breen & Goldthorpe, 1999), they were nonetheless able to rise through the ranks through a combination of talent and effort. We hypothesize that this was a result of great ambition and a willingness to prove themselves, which might have led to excessive risk-taking and profit-seeking in the run-up to the crisis. Stein (2007) presents a complementary interpretation of our findings. He linked the demise of Enron to the lack of a strong father figure who was unable to provide during the youth of the company's key players. This absence impeded the CEOs to accept authority later in corporate life, which is reflected in their contempt for auditors and regulators. Insofar as the father's employment status is related to him being a 'strong father', this might be the underlying mechanism explaining our findings.

Finally, we provide two alternative interpretations of our finding. If upper-class CEOs have greater opportunities to work for either weak or strong banks than lower-class CEOs, the upper-class CEOs – assuming they knew the strength of the banks –

refused to work for the weak banks and opted to work for the strong ones, while the lower-class CEOs were only offered jobs at the weak banks. Alternatively, weak banks, which were actively pursuing risky strategies, might only wanted to hire CEOs who were willing to execute these strategies. If the willingness to take such risks is related to class background this can also account for our finding.

2.5.3 Multivariate Analysis

In addition to the univariate analysis, we conducted a multivariate analysis, in which we relate the strength of a bank to the structure and agency variables. We employed a logit model and defined the continuous unobserved latent variable, $Strength_i^*$, such that it satisfies

$$Strength_i^* = \alpha + \beta Structure_i + \gamma Agency_i + \kappa Size_i + \varepsilon_i.$$

The link to the observed variable, $Strength_i$, is then given by

$$Strength_i = \begin{cases} 1 & \text{if} \quad Strength_i^* > 0, \\ 0 & \text{if} \quad Strength_i^* \leq 0, \end{cases}$$

where ε_i follows a logistic distribution with mean equal to 0 and standard deviation equal to 1. Since each bank is observed in five consecutive years, we allowed for correlation between these observations by clustering the error terms at the bank level. $Strength_i$ is equal to weak (0) or strong (1). $Structure_i$ is captured by the *Governance Index* and $Agency_i$ by the remuneration variables and the CEO's *Socioeconomic Background*. $Size_i$, as measured by the logarithm of the asset size,[33] is included to account for the correlation between the magnitude of the remuneration package and the size of the bank (Gabaix & Landier, 2008).

Before presenting the model estimations, we must note the following. The *CEO Duality* variable is not included in $Structure_i$ since the banks for which the CEO and

[33] A log transformation was applied to limit the impact of very large banks and bring the distribution closer to the normal distribution.

Chairman of the Board were not the same person are all weak banks, making it impossible to estimate this variable. Moreover, we had to interpolate the *Governance Index* variable, because it only had observations for 2002, 2004, and 2006. Since the index was determined in December of the years 2001, 2003, and 2005, we interpolated backwards and assumed that the index score in 2003 was equal to the score reported for 2004 and used the score reported for 2006 for 2005. The CEOs' *Socioeconomic Background* variable is not included in the first three specifications because the data on the CEOs fathers' professions was incomplete. In the fourth specification this variable is included which reduces the sample to 86 observations. In Table 2.8 we present the regression results.

Table 2.8. Results of a logit model relating the bank's strength to its structure and agency variables, while controlling for size. Weak banks are indicated by a 0 and strong banks by a 1. We report marginal effects of the variables and p-values are in parentheses. Standard errors are clustered at the bank level.

	I	II	III	IV
Governance Index	-0.0215	-0.0236	-0.0104	-0.0268
	(0.616)	(0.562)	(0.803)	(0.535)
Cash Bonus	-0.0156			-0.0274
	(0.245)			(0.167)
Delayed Bonus	0.0121			-0.00442
	(0.236)			(0.704)
Cash Bonus to Fixed Salary		-0.00550		
		(0.271)		
Cash Bonus to Delayed Bonus			0.0241	
			(0.201)	
Socioeconomic Background				0.318^{**}
				(0.022)
Log(Assets)	-0.270	-0.0995	-0.205	0.0124
	(0.363)	(0.679)	(0.409)	(0.967)
Observations	115	110	115	86

* $p < 0.10$, ** $p < 0.05$

We estimated four specifications of the model. The first contains the *Cash Bonus* and *Delayed Bonus* as a proxy for the $Agency_i$ dimension. In the second and third specifications, we include the *Cash Bonus* to *Fixed Salary* and *Cash Bonus* to *Delayed Bonus* variables, respectively, to measure the importance of short-term versus long-term incentives. Finally, in the fourth specification, we restrict the sample to observations for which the CEO's *Socioeconomic Background* is available.

We will compare the multivariate results with the univariate results. In Specification I, we observe a negative association between a bank's strength and the *Cash Bonus*, while we notice a positive association to the *Delayed Bonus*. In the second specification, the *Cash Bonus* to *Fixed Salary* ratio is negatively related to bank strength. Furthermore, in Specification IV, the CEO's *Socioeconomic background* is significantly positively related to the strength of the bank. These results are in line with the univariate results. In contrast to the univariate results, however, the *Cash Bonus* to *Delayed Bonus* ratio (Specification III) is positively related to the strength of the bank and the *Governance Index* is weakly negatively related. In sum, we conclude that the multivariate results are largely in line with the univariate results.[34]

2.5.4 Financial Characteristics

Univariate Analysis

In this section, we will compare the *Financial Characteristics* of weak and strong banks. In the next, we relate the strength of the banks to these financial characteristics using a multivariate analysis (see Arrow [2] in Figure 2.3).

[34]In unreported regressions, we also interacted the remuneration variables of Specifications I to III with the CEOs' *Socioeconomic Background* to assess whether the relationships differ for distinct class backgrounds. In the third specification, where the *Cash Bonus* to *Delayed Bonus* ratio is interacted with the CEOs' class background, the relationship is significantly negative for lower-class CEOs and insignificant for the other classes. The interaction terms in the other specifications all have insignificant coefficients with p-values of at least 0.3 and often even larger.

Table 2.9. *Financial Characteristics* of weak and strong banks. The weak and strong columns contain the averages for the variable listed. The p-value given corresponds to the Welch t-test (see Section 2.4.1).

Equity to Assets	weak	strong	p-value
2002	7.8%	8.3%	0.675
2003	7.7%	8.8%	0.299
2004	8.2%	9.4%	0.350
2005	8.0%	9.3%	0.333
2006	8.5%	9.5%	0.527
average	*8.0%*	*9.0%*	*0.404*

Tier 1 Ratio	weak	strong	p-value
2002	8.8%	11.6%	0.226
2003	9.2%	10.6%	0.260
2004	8.7%	10.8%	0.197
2005	8.3%	9.9%	0.120
2006	8.8%	9.8%	0.326
average	*8.8%*	*10.5%*	*0.129*

Debt to Assets	weak	strong	p-value
2002	38%	31%	0.350
2003	39%	31%	0.261
2004	40%	29%	0.234
2005	38%	32%	0.430
2006	36%	32%	0.558
average	*37%*	*31%*	*0.344*

Loans to Assets	weak	strong	p-value
2002	46%	38%	0.513
2003	48%	38%	0.397
2004	50%	39%	0.361
2005	51%	41%	0.348
2006	51%	41%	0.360
average	*49%*	*39%*	*0.390*

Return on Assets	weak	strong	p-value
2002	1.3%	1.4%	0.665
2003	1.4%	1.5%	0.891
2004	1.3%	1.6%	0.407
2005	1.3%	1.6%	0.244
2006	1.3%	1.9%	0.105
average	*1.3%*	*1.6%*	*0.342*

Return on Equity	weak	strong	p-value
2002	17%	17%	0.976
2003	19%	17%	0.558
2004	17%	17%	0.826
2005	17%	18%	0.530
2006	17%	21%	0.220
average	*17%*	*18%*	*0.733*

ST Debt to Assets	weak	strong	p-value
2002	25%	21%	0.685
2003	24%	20%	0.534
2004	22%	17%	0.397
2005	24%	17%	0.316
2006	21%	16%	0.445
average	*23%*	*18%*	*0.457*

Asset Growth	weak	strong	p-value
2002	10%	12%	0.697
2003	13%	11%	0.768
2004	24%	17%	0.345
2005	11%	11%	0.990
2006	16%	17%	0.838
average	*15%*	*14%*	*0.865*

Assets (in $ bn)	weak	strong	p-value
2002	279	217	0.587
2003	314	232	0.505
2004	389	303	0.618
2005	426	328	0.603
2006	502	377	0.568
average	*382*	*291*	*0.577*

* $p < 0.10$, ** $p < 0.05$

First, we notice that none of the tabulated differences is significant at the 10% level. However, for most of the variables, a consistent pattern can be observed. In accordance with our hypotheses, we found that weak banks were more highly leveraged than strong banks: the *Equity to Assets* and *Tier 1 Ratio* were lower for weak banks than for strong ones, and the *Debt to Assets* was higher. This suggests more funding risk at weak banks. The asset mix of weak banks was also riskier, as they had more loans on the balance sheet, which is in line with earlier results from Beltratti and Stulz (2012), Cole and White (2012), and Fahlenbrach et al. (2012). Even though strong banks were less risky, they performed better, as measured by the *Return on Assets*. However, the higher leverage ratio of weak banks almost entirely compensates for this difference, resulting in a similar *Return on Equity* for both groups. Moreover, weak banks financed a larger portion of their balance sheet with *Short Term Debt*, which has been identified as one of the causes of the crisis by Diamond and Rajan (2009). This exposed them to more liquidity risk. Limited to no support is found for the hypothesis of larger *Asset Growth* at weak banks. Finally, weak banks were 30% larger than strong banks. Based on these univariate results, we conclude that weak banks were riskier and less profitable than strong banks.[35]

In Section 2.2.2, following Calomiris and Haber (2014, pp. 258, 275–277), we associated the weak banks' pre-crisis outperformance to them being more risky and benefiting more from government subsidies. Our results are consistent with this explanation as weak banks invested more in risky assets, held less equity, relied more on short-term funding, and were larger. Despite their higher riskiness and larger government subsidies, weak banks were less profitable which is an indication of them having a lower franchise value than strong banks (Calomiris & Haber, 2014, pp. 275–276). We will now turn our attention to the multivariate results.

Multivariate Analysis

Now, we will relate the strength of a bank to its financial characteristics in a multivariate setting. We estimated a logit model as specified in Section 2.5.3, in which we replaced the structure and agency variables by *Financial Characteristics*. In principle, we used

[35]Note that eight of the 15 weak banks are categorized as weak because they failed the stress test. A bank failed this test if its capital ratios were insufficient under an adverse economic scenario. Since banks with lower capital ratios and more risky assets at the start of this scenario, and lower profitability during the downturn, were more likely to fail the test, the differences between weak and strong banks are consistent with this categorization criterion.

the same variables as reported in Table 2.9. However, in Specification I, we excluded *Debt to Assets* due to the large correlation with *ST Debt to Assets*. Similarly, the *Tier 1 Ratio* was excluded because it is closely related to *Equity to Assets*. Finally, *Return on Equity* was omitted because it is the multiplication sum of *Equity to Assets* and *Return on Assets*. In Specification II, *ST Debt to Assets* has been replaced by *Debt to Assets*, while in Specification III, *Equity to Assets* and the *Tier 1 Ratio* switch places.[36] *Size* is included as the logarithm of assets in all specifications. Results are reported in Table 2.10.

Table 2.10. Results of a logit model relating the bank's strength to its financial characteristics. Weak banks are indicated by a 0 and strong banks by a 1. We report marginal effects of the variables and p-values are in parentheses. Standard errors are clustered at the bank level.

	I	II	III
Equity to Assets	0.105**	0.0794*	
	(0.041)	(0.086)	
Loans to Assets	-0.0246**	-0.0234**	-0.0151
	(0.008)	(0.014)	(0.114)
Return on Assets	0.109	0.239	-0.0191
	(0.593)	(0.247)	(0.948)
ST Debt to Assets	-0.0184*		-0.0329**
	(0.084)		(0.011)
Asset Growth	-0.00547	-0.00326	-0.00278
	(0.212)	(0.296)	(0.401)
Log(Assets)	0.0415	0.01000	0.216
	(0.857)	(0.966)	(0.427)
Debt to Assets		-0.0162*	
		(0.096)	
Tier 1 Ratio			0.136
			(0.105)
Observations	115	115	85

* $p < 0.10$, ** $p < 0.05$

[36] Since investment banks and Washington Mutual do not disclose Tier 1 ratios, the sample size was reduced to 85 observations in Specification III.

We have three observations regarding these results. First, banks with lower funding risk – that is, a higher *Equity to Assets* or *Tier 1 Ratio* or lower *Debt to Assets* – are more likely to be strong. Second, *Loans to Assets* is negatively related to a bank's strength, which confirms the univariate finding that weak banks were more exposed to market risk. Third, banks financed with more short-term debt, and hence with a larger exposure to liquidity risk, are more likely to be weak. In sum, what Beltratti and Stulz (2012) showed for an international sample of large banks and Cole and White (2012) for a broad sample of U.S. banks, we have now shown for the 23 largest U.S. banks: crisis performance is negatively related to funding risk, market risk, and liquidity risk.

The simultaneous occurrence of lower riskiness at the strong banks and greater incidence of their CEOs being raised in the higher ranks of society poses a challenge to the finding of Kish-Gephart and Campbell (2015), namely that upper-class CEOs are more inclined to take risks. Future research is needed to uncover whether this discrepancy is due to the difference in samples or another reason.

2.6 Conclusion

In our study, we compared strong banks, which were able to endure the financial crisis on their own, to weak banks, which either went bankrupt, were acquired due to financial distress, or needed government support after failing the FED's stress test. Motivated by the sociological theory of structuration, in which structure, agency, and their interaction ultimately determine organizational outcomes, we argue that the strength of a bank is determined by the quality of its formal governance (structure) and behavior of its employees (agency). In our sample, however, the quality of formal corporate governance intended to ensure sound financial corporate strategy and execution could not explain the differences in strength. Meanwhile, behavioral aspects related to the banks CEOs might have played a role. The remuneration packages for CEOs at the weak banks were geared more towards the short term than the long term. Interestingly, we also found that

CEOs from weak banks were raised in lower socioeconomic environments significantly more often than those at strong banks.

In addition, weak banks were financed with more short-term and other forms of debt and less equity and had more loans on their balance sheet. Consequently, they were exposed to more liquidity, funding, and market risk. The 113% higher increase in stock returns for weak banks compared to strong ones prior to the crisis is likely to be a reflection of these higher risks. During the crisis, when the bad risks materialized, weak banks lost 94% of their market value, compared to "only" 71% for strong banks. The stock prices of strong banks have currently surpassed their pre-crisis levels, while those of weak banks remain below the starting point in 2000.

Appendix

A. U.S. Banking Sector

This appendix contains our specifications for the U.S. banking sector in 2006. Data were obtained from SNL Financial using the SNL Peer Analytics tool[37] with the following specifications:

- **Data Set** equal *GAAP/IFRS Companies*
- **Industry** in *Banking* + *Securities & Investments (only Broker-Dealer)* + *Specialty Finance (only Specialty Lender)*
- **Geography** in *United States*
- **Operating Status** in *Historical* + *Current*

We included the categories *Banking*, *Securities & Investments*, and *Specialty Finance* to identify all U.S. banks. For the *Securities & Investments* category only the *Broker-Dealer* subcategory was included and for the *Specialty Finance* category only the *Spe-*

[37] An account is required to use this tool.

cialty Lender subcategory was included. We restricted the selection to banks that were active in 2006. Moreover, we excluded institutions that were a subsidiary of a foreign bank or had no SIC code and those directly related to the government.[38] Furthermore, the SIC codes listed in Table A.1 were excluded because these types of institutions have a different focus and/or objective than the banks in our sample.[39]

Table A.1. SIC codes excluded to arrive at our definition of the U.S. banking sector.

SIC Code	SIC Description
6111	Federal & Federally Sponsored Credit Institutions
6141	Personal Credit Institutions
6159	Miscellaneous Business Credit Institution
6162	Mortgage Banker & Loan Correspondents
6172	Finance Lessors
6200	Security & Commodity Brokers, Dealers, Exchanges & Services

One peculiar organization remains in the list of banks after these exclusions: Navient Corp. The SIC code for Navient Corp. is 6211, that is, *Security Brokers, Dealers & Flotation Companies*, which is not a group that we excluded from our specification of the market. However, in 2006, Navient Corp. was still part of SLM Corp., which had an SIC code of 6141 (see `http://www.sec.gov/divisions/corpfin/organization/cfia-s.htm`). Since this code is for a type of company that we *did* exclude from our sample (see Table A.1), Navient Corp. was removed from our determination of the size of the market.

According to our definition of the U.S. banking market, the total market size in terms of assets equaled \$15,056bn in 2006. As a result, our 23 banks cover

$$\frac{\text{Total assets weak banks} + \text{Total assets strong banks}}{\text{Total assets U.S. banking market}} = \frac{\$7,535\text{bn} + \$3,019\text{bn}}{\$15,056\text{bn}} = 70\%$$

of the U.S. banking market (see Table 2.1).

[38]This restriction was only applied to the largest 42 institutions. As a result, we overestimated the size of the market. We expect this to have had a limited impact, however.

[39]See `http://www.sec.gov/info/edgar/siccodes.htm` for a list of the SIC codes.

B. Stock Price Indices

In Section 2.2.2, we compared the stock price indices of the weak and strong banks. This section discusses the approach used and accompanying assumptions made. First, dividends are directly reinvested – that is, at the end of the day, they have been distributed. Second, several comments need to be made regarding the constituents of the weak bank index. Lehman Brothers and Washington Mutual defaulted, and Merrill Lynch, Wachovia, Bear Stearns, Countrywide, and National City were acquired during the crisis as a result of financial distress. Although Lehman Brothers and Washington Mutual defaulted on September 15, 2008, and September 25, 2008, respectively, Bloomberg provided a stock price greater than 0 through March 6, 2012, for Lehman Brothers and March 21, 2012, for Washington Mutual. We used those prices until they were no longer available, after which they were set to 0. Concerning the acquisitions of Merrill Lynch, Wachovia, Bear Stearns, Countrywide, and National City, prices were available past the date the acquisition was announced (see Table B.1). We used those prices until they were no longer available. After that, the share price of the acquired company was computed as the share price of the acquiring company multiplied by the number of shares that the acquiring company paid for the acquired company. See Table B.1 for an overview of the acquisitions and the corresponding information, which was obtained from press releases and Bloomberg.

Table B.1. Banks acquired due to financial distress. A list of banks acquired during the financial crisis, along with the acquiring companies, the number of shares in the acquiring company per share held in the acquired company, the announcement date, and the date of the final stock quote in Bloomberg.

Acquired Company	Acquiring Company	# Shares	Announcement Date	Final Stock Quote
Merrill Lynch	Bank of America	0.8595	September 15, 2008	January 2, 2009
Wachovia	Wells Fargo	0.1991	October 3, 2008	January 2, 2009
Bear Stearns	JPMorgan Chase	0.21753	May 29, 2008	June 6, 2009
Countrywide	Bank of America	0.1822	January 11, 2008	July 1, 2008
National City	PNC Financial	0.0392	October 24, 2008	December 31, 2008

3 When are Pre-crisis Winners Post-crisis Losers?

Co-Authors: Kees Cools and Arthur van Soest

Abstract

Which banks failed to recover from the financial crisis and why? For the U.S., we present strong evidence that the best performers pre-crisis (2000 through December 2006) have been the worst performers since the crisis (March 2009 through 2015). In Europe, the best performers from before the crisis (2000 through July 2007) continued to perform best afterwards (March 2009 through 2015). In our analysis, we account for known risk factors from the start of the crisis, such as beta, size, book-to-market, leverage, composition of assets and liabilities, and short-term funding. In both the U.S. and Europe, high pre-crisis bank returns are paired with high-risk characteristics. We argue that the high-performing U.S. banks from before the crisis were unable to fundamentally transform or adapt their risky business model afterwards and have subsequently become post-crisis laggards.

3.1 Introduction

How did banks that were high-performing before the 2007–2008 financial crisis perform afterwards and why? In the aftermath of the crisis, we have obtained a clearer indication of some of the basic building blocks underlying banking sector economics prior to

2007. On the asset side, banks used aggressive sales tactics to sell mortgages with harsh conditions to unsophisticated clients of dubious credit worthiness (Agarwal, Amromin, Ben-David, Chomsisengphet, & Evanoff, 2014). One part of these assets was off-loaded from the balance sheet through the securitization process, by selling them to investors. Moreover, in the selling process, underwriters and credit agencies misrepresented the quality of the underlying mortgages to investors (Griffin & Tang, 2012; Piskorski, Seru, & Witkin, 2015), and banks exerted less effort in monitoring the securitized loans than those kept on the balance sheet (Keys, Mukherjee, Seru, & Vig, 2010). For the remaining part, banks kept mortgages and mortgage backed securities on their balance sheet (Acharya, Richardson, Van Nieuwerburgh, & White, 2011, pp. 49–50; Calomiris, 2009; Calomiris & Haber, 2014, p. 262) or put them into conduits (Acharya, Schnabl, & Suarez, 2013; Gorton & Metrick, 2012) in order to profit from the mortgage risk while circumventing stringent capital requirements.

The securitization of mortgages was the rule rather than the exception before the crisis: in 2006, around 56% of all outstanding residential mortgages and more than two-thirds of subprime mortgages were securitized (The Economist, 2007). Shleifer and Vishny (2010) used a theoretical model to show the attractiveness for banks of securitization when investor demand is high. In order to earn as much profit as possible, banks stretched their balance sheet through short-term debt, even though this increased their riskiness (Demirgüç-Kunt & Huizinga, 2010) and exposed them to losses in a downturn (Rajan, 2006; Shleifer & Vishny, 2010). These dynamics of excessive short-term risk-taking, with possible long-term negative consequences, are also evident in the labor market model of investment banking managers (Acharya, Pagano, & Volpin, 2016). Low-skilled managers try to hide their inability by investing in projects that will pay off in the short run (interest on a mortgage-backed security) but may possibly carry heavy losses in the long run (default of the mortgage). The possibility of being poached by another bank affords them an escape route, delaying revelation of their true inability.

A related fundamental problem in the run-up to the crisis was the presence of high leverage ratios. Berger, Herring, and Szegö (1995) show that the equity to assets ratio for U.S. commercial banks decreased steadily throughout the last century, from around 20% in 1900 to between 6% and 8% toward the end of the century. As convincingly argued by Admati and Hellwig (2013), low levels of equity on the liabilities side increase returns, but likewise increase risks. However, since banks benefit from explicit and implicit government guarantees [the value of which was equal to over $100bn for shareholders alone at the height of the crisis (Kelly, Lustig, & Van Nieuwerburgh, 2011)], part of this risk is born by taxpayers.

In addition to the short-term gains earned through securitization and increased leverage, there was a pattern of widespread malfeasance: Zingales (2015b) documents fines for banks' malpractices in terms of Libor and Euribor rate setting and discrimination in providing loans. The trade-off between gains in the short term and losses in the long term was starkly expressed by the CEO of Citigroup, Chuck Prince, in an article in the *Financial Times*: "When the music stops, in terms of liquidity, things will be complicated. But as long as the music is playing you've got to get up and dance. We're still dancing" (Nakamoto & Wighton, 2007).

One would expect banks that engage in relatively high volumes of risky activities funded by large amounts of short-term debt and little high-quality capital, yet supported by implicit government guarantees, to generate high stock returns. Conversely, when collateral values suddenly drop, risk premiums surge, interest rates for short-term funding rise, counterparties default or cannot meet their obligations, and a financial crisis is immanent, one would expect these same institutions to suffer the most and have among the poorest stock returns.[1] But once the crisis has reached its lowest point and

[1] See Calomiris (2009), Brunnermeier (2009), Gorton and Metrick (2012), Lo (2012), and Calomiris, Eisenbeis, and Litan (2012) for excellent expositions on the dynamics leading up to the crisis and of its unfolding and, subsequently, the real effects for the economy. In addition, Rajan (2006) is an interesting read for the special attention given to distortive incentives in the financial system before the crisis. Alternatively, Tuckett (2011) provides a psychoanalytic explanation for the development of the pre-crisis mortgage bubble. In short, he argues that a sufficiently large group of market participants was

stock prices have started to recover, how do the banks with riskier business models and a high risk culture perform?[2] Do they then again start reaping the benefits of their high risk–high return profile and showing superior stock returns once more (what we will refer to here as the "high risk–high reward" hypothesis)? Or do they encounter sustained difficulties in recuperating and restoring trust amongst their former and existing clients and counterparties and consequently show persistently low returns (what we call the "boom-and-bust" hypothesis)? The rationale for this second scenario would be that many of the highly profitable pre-crisis financial instruments and practices are no longer allowed or possible post-crisis; yet at the same time, such banks find it difficult to adapt to the new environment by changing their business model (Fahlenbrach et al., 2012). The pre-crisis high risk–high reward banks being forced to fundamentally change their business model and risk culture to satisfy regulators, investors, clients, and taxpayers may well be willing but simply unable to do so. Consequently, the loss of significant pre-crisis profit pools combined with an inability to change their business model results in lagging stock returns.

We empirically tested these two hypotheses against each other and found evidence for the U.S. that is strongly supportive of the boom-and-bust hypothesis. Using a sample of 354 U.S. banks, we show that superior pre-crisis stock performance (2000–December 2006) is a strong predictor of poor post-crisis stock performance (March 2009–2015). We controlled for risk characteristics in all specifications. The main result holds regardless of whether we included investment banks in our sample or not. Our key result is that, in the cross section, a one-standard-deviation higher stock return before the crisis,

attracted to the "phantastic object" of mortgage backed securities, which led to "groupfeel" and the denial of associated risks.

[2]In order to benchmark our approach, we have searched for studies that compared pre- and post-crisis stock performance for industrial firms. Unfortunately, we have not been able to find these. However, one study, Claessens, Djankov, and Xu (2000), focused on industrial firm's profitability before and after the East Asian Financial Crisis and documented a significant positive relationship. This is consistent with the explanation that firms of higher quality perform better both before and after a crisis. Insofar strong stock performance before the crisis would also be a reflection of high firm quality, we would expect a positive association between pre- and post-crisis performance. However, if pre-crisis stock performance is not directly related to quality but, for instance, to taking excessive, non-sustainable risks, we expect a negative association.

ceteris paribus, predicts a 36% lower return after the crisis. Earlier studies (e.g., Beltratti & Stulz, 2012; Fahlenbrach et al., 2012) have found that high pre-crisis returns for banks were predictive of poor stock performance during the crisis. We similarly found that U.S. banks with a high pre-crisis risk profile that generated high stock returns in the run-up to the crisis were also the worst performers during the crisis itself (2007–2009).

To better understand the characteristics of pre-crisis high-performing banks, we regressed 2000–2006 stock returns on the pre-crisis attributes of these banks. We found that banks that performed well before the crisis showed signs of having a high-risk business model or culture: they had high funding fragility, low levels of securities as a percentage of total assets, and a fast-growing loan book.

Our findings for U.S. banks raise the following question: *Why* are pre-crisis winners post-crisis losers? The negative relationship between pre- and post-crisis stock returns we found for the U.S. seems to be mediated by pre-crisis loan growth. We argue that this variable reflects the level of participation in the pre-crisis mortgage boom – directly by holding risky mortgage loans and indirectly through the shadow banking system. Various legal measures and regulations in the aftermath of the crisis, such as Basel III and the Dodd-Frank Act, and regulators' increased scrutiny of both observable risks (e.g., capital and liquidity levels) and previously non-observable risks (e.g., various elements of shadow banking) (Financial Stability Board, 2015) make it much harder for banks to depend on associated profit pools to perform. This is a probable driver of their lagging post-crisis stock returns.

For the 218 banks in our European sample, we found that the best performers pre-crisis were also the best performers post-crisis, opposite to our finding in the U.S. However, similar to in the U.S., in Europe, we found a negative relationship between pre-crisis returns and returns during the crisis. Moreover, as in the U.S., the pre-crisis stock returns of European banks are associated with higher levels of risk, such as high fragility in funding, a lower securities to assets ratio, and high loan growth. This suggests that, contrary to their U.S. peers, European banks that performed well prior to the crisis were able to adequately adjust their business models afterwards or did not need to change (as much as their U.S. counterparts) because they were already operating in line with the post-crisis environment.

Our study is related to the work of Fahlenbrach et al. (2012), who investigated the persistence of bank performance across crises. They showed that U.S. banks that performed badly during the 1998 Russian financial crisis performed badly again in the 2007–2008 financial crisis and concluded that the risk culture of banks is not easy to change, thus refuting the alternative learning hypothesis, which states that banks that perform badly in a crisis will learn from that experience and improve their performance the next time. Whereas Fahlenbrach et al. studied bank performance across different crises, we relate the pre-crisis stock performance of banks to their performance after that same crisis. Nevertheless, the underlying mechanism of an inability and/or unwillingness on the part of banks to change their business model – one possible explanation for the findings of Fahlenbrach et al. – might also explain our main result. The banks that performed the best before the crisis and needed to change their business model and risk culture the most afterwards struggled to do so, and as a result, systematically underperformed.

To the best of our knowledge, this is the first study to investigate the relationship between pre- and post-crisis stock returns of banks. There are, however, studies that have tried to explain cross-sectional bank stock returns *during* the financial crisis itself by looking at pre-crisis risk factors and governance attributes (e.g., Beltratti & Stulz, 2012; Ellul & Yerramilli, 2013; Erkens et al., 2012; Fahlenbrach & Stulz, 2011). In general, they have found that higher risk before the crisis was related to lagging stock returns during the crisis. Demirgüç-Kunt, Detragiache, and Merrouche (2013) compared the relationship between quarterly stock returns and bank characteristics before and during the crisis. Whereas they found no link between pre-crisis stock returns and pre-crisis capital levels, they did find a negative link between crisis capital levels and crisis stock returns. Moreover, a greater reliance on deposits and less liquid assets were associated with higher returns during the crisis. Besides stock performance, there have been alternative ways used to measure cross-sectional bank performance during the crisis. Berger and Bouwman (2013), for example, used bank survival and market share expansion as performance criteria and showed that well-capitalized banks performed better. Alternatively, Altunbas, Manganelli, and Marques-Ibanez (2011) used capital or liquidity support from the government as a dependent variable and found that nondeposit short-term funding was positively related to the acceptance of government support and capital negatively related.

Next, this study builds on Fahlenbrach, Prilmeier, and Stulz (2016), who document that fast-growing U.S. banks in a three year period have lower stock returns in subsequent years than slow-growing banks. We extend their finding by showing that pre-crisis loan growth seems also to have hampered U.S. banks' ability to recover up to eight years after the start of the recent financial crisis.

Finally, this study is related to the literature on banking crises, which we divide into three categories. The first category contains research on the causes of banking crises, such as that by Reinhart and Rogoff (2011). Besides this strain of research identifying causes, studies such as that of Kaminsky and Reinhart (1999) document how macroeconomic variables behave after such crises. These two categories deal with country-level aggregates, however, while our focus is on the bank level. This approach was adopted by Demirgüç-Kunt, Detragiache, and Gupta (2006), who documented the negative impact of banking crises on bank profitability. In contrast to their approach, we focus on the relationship between bank stock performance before and after one specific banking crisis.

In Section 3.2, we discuss the sample, introduce the main dependent and independent variables, and present summary statistics. Sections 3.3 and 3.4 report the results for the U.S. and Europe, respectively. In Section 3.5, we perform some robustness checks.

Section 3.6 concludes.

3.2 Data

In this section, we describe the sample selection, dependent and independent variables, and summary statistics.

3.2.1 Sample Construction

We focus on U.S. and European banks, since the financial crisis started in the U.S. and spread quickly to the European region due to close ties between the two financial markets. Furthermore, at the start of 2016, the U.S. and European banking sectors together comprised more than 50% of banking assets worldwide (see `http://www.eiu.com/industry/Financial-services#`). We used Bankscope to identify all listed banks with assets over \$500 million on December 31, 2006. These restrictions resulted in the sample presented in the top line of Figure 3.1.

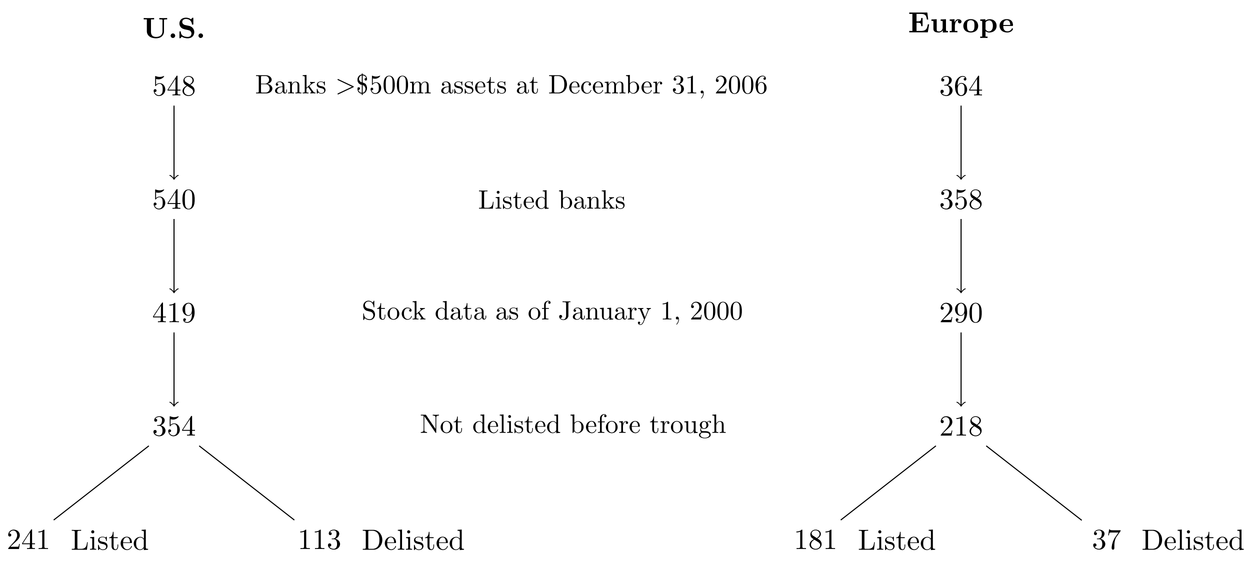

Figure 3.1. Listed and delisted U.S. and European banks with assets over \$500m as of December 31, 2006. In the first step, banks dropped out because there was no stock data available on Datastream. In the second step, banks that were not yet listed on January 1, 2000 were deleted. The third step excluded banks that had been delisted before the end of the crisis (i.e., March 2009).

The banks from Bankscope were then linked to banks in Datastream using the International Securities Identification Number (ISIN). Banks for which there was no stock data available in Datastream were deleted in the first step. In the second step, banks for which no stock price was available at the start of the pre-crisis period (January 1, 2000) were dropped. In the third step, we deleted banks that were delisted before the end of the crisis. This left us with a sample of 354 U.S. and 218 European banks: 113 of the 354 U.S. banks were delisted between the 2009 trough and the end of the sample period (May 22, 2015), while the rest were listed over the entire time period; 181 banks of the 218 European banks were listed continuously, and 37 were delisted.[3] We do not separately consider the three different causes of delisting (i.e., bankruptcy, merger or acquisition, or going private) in our analysis. Table 3.1 provides an overview of the sample banks per country and shows the division between the listed and delisted categories.

[3] In the U.S., the proportion of delistings is almost twice as high as in Europe. An explanation could be the reluctance of European governments and / or regulators to let banks fail because of their strong political connections. This might have played a more limited role in the U.S., which is potentially related to the smaller U.S. than European banks in our sample.

Table 3.1. Sample banks per country, categorized as listed or delisted. Banks for which buy-and-hold stock returns are available from January 1, 2000, through May 22, 2015, are categorized as listed. Banks for which stock returns are available from January 1, 2000, to the point of their delisting (after the crisis) are categorized as delisted.

Country	Total	Listed	Delisted
Austria	7	7	0
Belgium	5	5	0
Cyprus	4	2	2
Denmark	18	12	6
Finland	3	2	1
France	24	20	4
Germany	10	8	2
Greece	11	7	4
Ireland	3	3	0
Italy	20	16	4
Liechtenstein	2	2	0
Luxembourg	2	1	1
Monaco	1	1	0
Netherlands	6	5	1
Norway	15	15	0
Portugal	4	2	2
Spain	9	4	5
Sweden	6	6	0
Switzerland	24	22	2
Turkey	12	10	2
United Kingdom	32	31	1
Europe	218	181	37
United States	354	241	113

The totals for the U.S. and Europe correspond to the totals of the last lines in Figure 3.1. Although the overall banking market in Europe is much larger than in the U.S. (currently three times larger in terms of assets, see `http://www.eiu.com/industry/Financial-services#`), our sample contains more U.S. banks. There are two reasons for this: 1) U.S. banks are listed more frequently, and 2) U.S. banks are smaller than European banks.

3.2.2 Dependent and Independent Variables

The main dependent variable we consider throughout the chapter is the stock return after the crisis, *Returntrough2015.* The trough is defined as the lowest level of the unweighted average stock returns of our sample banks after the crisis. Although we treat the U.S. and Europe separately, the trough for both groups coincides: March 9, 2009. Our main explanatory variable is the buy-and-hold stock return between January 1, 2000, and the pre-crisis peak, *Return2000peak.* Similarly to the trough, the peak is defined as the highest level of the unweighted average stock returns of our sample banks before the crisis, calculated separately for the U.S. and Europe. For the U.S. sample banks, this is December 28, 2006, while for Europe, the peak is attained on July 19, 2007.

In addition to post-crisis returns, we use the returns during the crisis (from the peak to the trough), *Returnpeak_trough*, as a dependent variable. In this way, we can relate our results to the findings of Fahlenbrach et al. (2012) and Beltratti and Stulz (2012). The aforementioned discussion is graphically summarized in Figure 3.2.

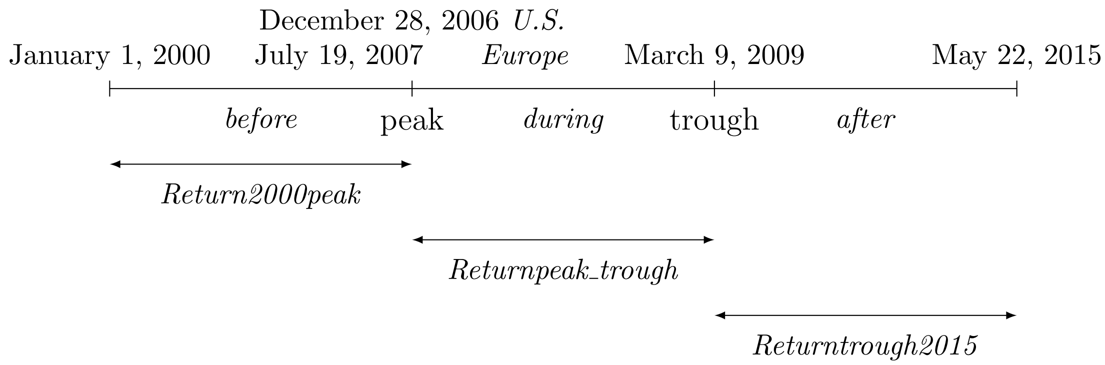

Figure 3.2. The time periods *before*, *during*, and *after* the crisis and the corresponding return variables.

For banks that were delisted after March 9, 2009, we set the return equal to their return up to delisting, that is, their return is set to zero after delisting. Delistings occur for different reasons, but we expect the main cause to have been financial distress in our sample period. In such cases, the delisted bank does not "perform" anymore after delisting, which motivates the decision for setting the return at zero. This reasoning is less applicable for banks that were acquired or taken private, however. To alleviate these concerns, therefore, we perform robustness tests in Section 3.5.2, where delisted banks are deleted from the sample altogether or the return of delisted banks as of delisting is extended with a financial index return.

Bank performance during and after the crisis is obviously related to not only pre-crisis returns, but also other bank characteristics in general and a bank's riskiness in particular. We therefore include as control variables bank characteristics from just before the crisis that have been shown to be relevant to bank performance and riskiness. Following Fahlenbrach et al. (2012), we control for beta, size, book-to-market of equity, and market value of leverage. We estimate beta from a weekly CAPM regression model from 2003 to 2006. Size is measured by the market capitalization of equity, and we apply a log transformation to adjust for the positive skewness of the distribution and limit the impact of very large banks. Book-to-market is the book value of common equity to the market value of common equity. Finally, we use the market value of leverage, MVLeverage, as defined in Acharya et al. (2017).[4] Berger and Bouwman (2013) have shown a positive relationship between a bank's equity ratio (i.e., the inverse of the leverage ratio) and its performance (measured in terms of probability of survival and market share) during banking crises. Moreover, for small banks, capital is always positively related to performance (i.e., not only during banking crises). Beltratti and Stulz (2012) have corroborated this finding for large international banks during the financial crisis, and Fahlenbrach et al. (2012) have done so for a sample of U.S. banks. Finally, Cole and White (2012) have documented greater chances of survival for better capitalized banks.

We include three other variables related to bank performance in our main regressions: funding fragility, securities, and illiquidity. Funding fragility is the proportion of non-

[4]In our baseline specification, we rely on the market value of equity instead of the book value to compute our measure of leverage. Calomiris and Herring (2013) showed the discrepancy between the book value of equity and the true capital strength of banks before and during the crisis, which ex post turned out to be better reflected by the market value of equity.

deposit short-term funding to total short-term funding (including deposits) (Demirgüç-Kunt & Huizinga, 2010). Shleifer and Vishny (2010) demonstrated that banks' reliance on nondeposit short-term funding was an important factor in the destabilization of the banking sector and was associated with higher risk (see also Altunbas et al., 2011), while Demirgüç-Kunt et al. (2013) and Beltratti and Stulz (2012) showed that a higher level of deposit funding (the flipside of nondeposit short-term funding) was associated positively with returns during the crisis.

Another criterion we use to gauge the banks' activities is the proportion of securities to assets. Since a bank's balance sheet is mainly composed of securities and loans, this variable is roughly the complement of loans to assets. Although the trigger of the financial crisis was mortgage-backed securities (Brunnermeier, 2009, pp. 82–84), Beltratti and Stulz (2012) found a negative relationship between loans and crisis stock returns and Altunbas et al. (2011) documented a positive relationship between loans and riskiness.

The third variable, illiquidity, measures the difficulty a bank might experience in repaying short-term liabilities in the event of distress. A high value indicates a high level of nondeposit short-term liabilities in relation to liquid assets, which can lead to trouble in refinancing the liabilities when these wholesale funding markets experience distress (Brunnermeier, 2009). However, surprisingly, Demirgüç-Kunt et al. (2013) found a positive relationship between illiquidity and stock performance during the crisis. This is ascribed to mortgage-backed securities being classified as liquid assets, which turned out to be less liquid when the crisis struck, and to the increases in banks' liquidity provided by the central banks, which could have been interpreted by markets as a signal of weakness.

In some regressions, leverage is replaced by the Tier 1 Ratio, which then automatically excludes investment banks and government-sponsored entities from the sample (e.g., Fannie Mae and Freddie Mac for the U.S. and Nationale Bank van België and

Schweizerische Nationalbank for Europe). Beltratti and Stulz (2012) found a negative relationship between Tier 1 Ratio and stock returns during the crisis, and Altunbas et al. (2011) have demonstrated a negative relationship between risk and this capital ratio. Unless stated otherwise, all explanatory variables, except for stock returns, are measured as of December 31, 2006. A description of all variables can be found in Appendix A.

We obtained data from Bankscope, except for the market capitalization and stock returns data, for which we used Datastream. For the latter, we used the Total Return datatype of Datastream, which takes the reinvestment of dividends and stock splits into account. The data from Bankscope can be linked to that from Datastream using the International Securities Identification Number (ISIN). In some cases, the Bankscope ISIN did not match the Datastream ISIN. To ensure correspondence between data from both databases, we then verified the asset size of the bank found in Datastream with the one provided by Bankscope.

3.2.3 Summary Statistics

Before we present summary statistics for U.S. and European banks we show the trajectory of stock prices over the period studied. Figure 3.3 is the unweighted average for U.S. and European banks in our sample from 2000 to 2015 (see Appendix B for modifications to the stock price data).

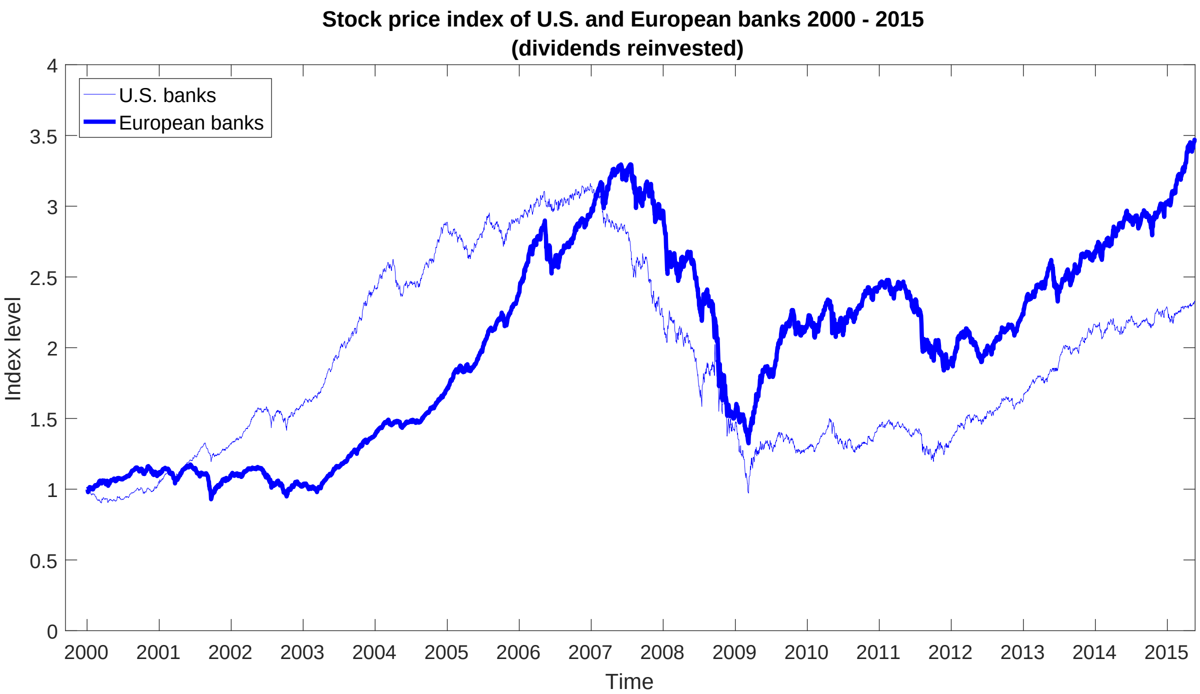

Figure 3.3. Stock prices, adjusted for reinvestment of dividends and stock splits, for the unweighted index of U.S. banks (thin line) and European banks (thick line) from 2000 to 2015. The returns for banks delisted after the trough is set to zero, since Datastream stops providing data as of that moment.

Although the phases of the trajectories are similar, there are some differences between U.S. and European banks. First, while U.S. bank stock returns increase continuously from the start of the sample period to the peak at the end of 2006, the sustained increase of stock returns at European banks starts three years later, in the first quarter of 2003.[5] Second, stock prices of European banks attain their peak more than six months after U.S. banks, and the increase before the crisis is somewhat larger in Europe (230%) than in the U.S. (216%). Third, European banks' stock returns have recovered significantly better from the crisis than their U.S. counterparts: 162% for Europe versus 139% for the U.S. Note that the 2011–2012 Eurozone crisis is visible for the European banks, but not for U.S. banks. Despite those losses, though, European banks have come out of the financial crisis stronger compared to their transatlantic counterparts.[6] Hence, the Euro-

[5]In the U.S. and in Europe, as of the start of 2003, stock prices increase sharply. We interpret this using the psychoanalytic analysis of bubble formation developed by Tuckett (2011): the acceleration of stock returns might have been the result of the spread of the belief in the "phantastic object" (i.e., mortgage backed securities) to an ever broader group of market participants. This belief ultimately led to "groupfeel" and herding behavior, that is, widespread exposure to the mortgage market.

[6]This contradicts the common view that European banks lag behind U.S. banks. In The Economist

zone crisis period, studied by Hoque (2013) and Hoque, Andriosopoulos, Andriosopoulos, and Douady (2015), was confined to European banks and the associated decline in stock prices was much smaller than during the financial crisis.

We go on below to present the summary statistics for the main variables used throughout the chapter. Table 3.2 contains the summary statistics for U.S. banks, followed by Table 3.3, with those for European banks.

Table 3.2. Sample summary statistics of U.S. banks. Variable definitions can be found in Appendix A. Accounting variables are measured as of December 31, 2006.

	Number	Min	25% Quantile	Median	75% Quantile	Max	Mean	SD
Returntrough2015	354	-1.00	0.14	1.13	2.36	23.52	1.71	2.77
Returnpeak_trough	354	-1.00	-0.88	-0.69	-0.48	0.27	-0.65	0.27
Return2000peak	354	-0.33	0.84	1.60	2.69	40.74	2.16	2.89
Book-to-market	352	0.14	0.44	0.56	0.71	184.13	1.21	9.92
log[Market cap (in $m)]	352	-1.02	4.70	5.36	6.89	12.52	5.97	1.86
Market cap (in $m)	352	0.36	110.43	213.28	986.30	274,296.40	5,315.15	24,322.51
Beta	354	-16.64	0.11	0.40	0.87	2.20	0.46	1.03
MES	354	-0.03	-0.01	-0.01	-0.00	0.01	-0.01	0.01
MVLeverage	352	1.04	6.63	8.46	10.80	2,325.08	17.66	126.95
BVLeverage	354	1.14	9.68	11.35	13.20	31.63	11.71	3.53
TCE Ratio	354	-0.12	0.06	0.07	0.09	0.84	0.08	0.05
Tier 1 Ratio	304	0.06	0.10	0.11	0.13	0.27	0.12	0.03
Assets (in $m)	354	500.63	750.99	1,265.99	6,043.90	1,884,318.00	36,103.17	178,354.75
Loans	354	0.00	0.61	0.71	0.77	0.92	0.67	0.18
Securities	354	0.00	0.11	0.17	0.26	0.89	0.20	0.14
Risk weight	299	0.41	0.68	0.77	0.84	1.22	0.76	0.12
Customer deposits	354	0.00	0.67	0.74	0.81	0.90	0.70	0.20
Funding fragility	352	0.00	0.03	0.07	0.12	1.00	0.13	0.21
Illiquidity	354	0.00	0.43	1.23	3.01	48.97	2.34	3.88
IV	354	0.02	0.04	0.05	0.07	11.85	0.15	0.70

The median book-to-market ratio of the banks in our sample is 0.56. The market capitalization equals $213m for the median bank. Median beta equals 0.40, which is considerably lower than 1. An alternative measure for systematic risk is the marginal

(2017b) the stock price development of the largest U.S. and European banks were compared. The difference with the course of our indices is mainly caused by two factors. First, the S&P 500 banks index and STOXX Europe 600 banks index, that is, the ones used in the The Economist, are composed of 71 and 45 banks, respectively, while we consider 354 U.S. and 218 European banks. Second, we use the equal weighted average of the banks in our sample, while the well-known indices use the market capitalization weighted average. Based on the graph from The Economist, we conclude that large U.S. banks had more difficulty recovering just after the crisis [potentially related to the major, forceful recapitalization of the banks (The Economist, 2017a)], but when the Euro crisis spread, these U.S. banks caught up and outperformed their European counterparts as of the second half of 2011. The slow economic recovery and the delayed recognition of bad loans at Europe's large banks (The Economist, 2017a) potentially explains their lagging stock returns as of that period.

expected shortfall (MES) of Acharya et al. (2017), which measures a bank's performance during the 5% worst days of market performance from 2003 to 2006: the median bank had a return of -0.51% during those days. We use four capital ratios to gauge the financial robustness of a bank. Following Acharya et al. (2017), we define the market value of leverage (MVLeverage) as total assets minus the book value of equity plus the market value of equity, divided by the market value of equity. Alternatively, we consider the book value of leverage (BVLeverage), which is the proportion of assets to the book value of equity. The median bank has a lower market value of leverage (8.46) than book value of leverage (11.35), which is consistent with a median book-to-market ratio of 0.56.[7] The third capital ratio is the amount of tangible common equity to tangible assets, TCE Ratio, which equals 7.3% for the median bank. The fourth ratio is the amount of regulatory Tier 1 Capital to risk-weighted assets, the Tier 1 Ratio. For the U.S., the median Tier 1 Ratio equals 11%, which is nearly three times the minimum requirements of Basel I and II, while the bank with the lowest Tier 1 Ratio, at 6%, still considerably exceeds those regulatory requirements (the minimum Tier 1 Capital Ratio prescribed in the Basel I and II Accords was 4%). The median bank has $1.3bn assets, but there is a large variance in size: the smallest bank in our sample has $501m assets and the largest bank $1,884bn.

The banks in our sample hold many more loans (median of 71%) on their balance sheet than securities (median of 17%). The risk weights of assets variable for the median bank equals 77%, that is, every dollar of assets counts for 0.77 dollar in the computation of the risk-adjusted assets. These risk-adjusted assets are the denominator in the Tier 1 Ratio. On average, 74% of the median balance sheet is funded with customer deposits. Furthermore, only a small portion of total short-term funding (i.e., including deposits) is funded with nondeposit funds, such as money-market funds. Hence, the funding fragility at our median bank is only 7%. A large variance exists in the proportion of liquid assets for honoring short-term obligations. The illiquidity variable ranges from 0 (no short-term

[7] A book-to-market ratio of 1 would imply equality between the market and book value of equity and thus equality of the market and book value of leverage. Since the market value of equity is mostly larger than the book value, the book value of leverage is in most cases larger than the market value.

liabilities) to 48.97 (48.97 dollars of short-term liabilities to every dollar of liquid assets). An alternative measure of bank risk is the idiosyncratic volatility (IV) of bank returns, measured by the nonsystematic variability in stock returns.

Finally, we take a closer look at the outliers in our sample. The maximum values for our main dependent variable, *Returntrough2015*, and independent variable, *Return2000peak*, equal 23.52 and 40.74, respectively. Considering that the medians for these two variables are 1.13 and 1.60, respectively, these are outliers. Moreover, many other variables, most notably Book-to-market, MVLeverage, Beta, and Illiquidity, also have outliers. The sensitivity of OLS estimates to outliers motivates us to check whether our main results remain valid when we Winsorize the data at the 1% level.

Table 3.3. Sample summary statistics of European banks. Variable definitions can be found in Appendix A. Accounting variables are measured as of December 31, 2006.

	Number	Min	25% Quantile	Median	75% Quantile	Max	Mean	SD
Returntrough2015	218	-1.00	0.10	1.01	2.73	13.73	1.69	2.43
Returnpeak_trough	218	-0.99	-0.78	-0.62	-0.45	0.18	-0.58	0.26
Return2000peak	218	-0.83	0.56	1.34	2.55	21.78	2.30	3.11
Book-to-market	213	0.14	0.39	0.53	0.91	168.02	1.96	11.75
log[Market cap (in €m)]	213	2.91	5.93	7.07	8.47	11.98	7.24	1.96
Market cap (in €m)	213	18.42	375.15	1,176.81	4,791.15	159,906.31	8,507.48	20,328.94
Beta	218	-0.26	0.13	0.46	0.80	1.82	0.50	0.43
MES	218	-0.04	-0.02	-0.01	-0.00	0.01	-0.01	0.01
MVLeverage	213	1.01	5.28	10.54	17.88	1,809.60	28.16	139.18
BVLeverage	218	1.02	7.34	12.28	17.84	107.10	14.29	11.71
TCE Ratio	218	-0.07	0.05	0.07	0.12	0.98	0.15	0.23
Tier 1 Ratio	119	0.06	0.07	0.09	0.11	0.34	0.10	0.05
Assets (in €m)	218	388.14	2,188.60	7,838.34	40,181.10	1,571,768.00	105,400.03	285,382.52
Loans	218	0.00	0.30	0.60	0.75	0.94	0.51	0.29
Securities	218	0.00	0.07	0.16	0.31	0.99	0.24	0.25
Risk weight	113	0.15	0.50	0.63	0.76	1.33	0.62	0.21
Customer deposits	218	0.00	0.19	0.42	0.56	0.89	0.38	0.25
Funding fragility	206	0.00	0.11	0.26	0.50	1.00	0.35	0.30
Illiquidity	216	0.00	0.27	0.72	1.80	91.26	2.37	7.35
IV	218	0.01	0.03	0.04	0.05	0.12	0.04	0.02

In discussing the characteristics of European banks, we focus on the differences with U.S. banks. First, European banks are much larger on average than U.S. banks: their median market capitalization is more than seven times higher than that of U.S. banks and their median asset size more than eight times higher. Second, the median European bank is funded with only 42% customer deposits, compared to 74% for the median American bank, indicating that the funding fragility of European banks is higher. Third, European banks also seem more fragile than their American counterparts in terms of capital ratios. However, one must be cautious when comparing the summary statistics of capital ratios between the U.S. and Europe because of differences in the accounting standards used. Financial institutions in the U.S. use Generally Accepted Accounting Principles (U.S. GAAP), whereas in Europe, the International Financial Reporting Standards (IFRS) prevail. Admati and Hellwig (2013, pp. 83–85) have pointed out that in the case of JP Morgan Chase, for example, total assets on December 31, 2006, would have been 79% higher based on IFRS compared to U.S. GAAP. The main two reasons for such large differences are that in the U.S. more assets can be removed from the balance sheet and derivatives of the same counterparty on the assets and liabilities side of the balance sheet can be cancelled out (so-called netting). The IFRS framework has more restrictions in these respects.

Supposing the U.S. GAAP versus IFRS difference for JPMorgan Chase were to be extended to our sample of banks, the IFRS-consistent value of assets would increase by 79%, as well. Correspondingly, the median Tier 1 Ratio of 11.1% of U.S. banks would decrease to (11.1%/1.79=) 6.2%, which is 2.7 percentage points lower than the 8.9% for European banks.[8] Although it can be expected that JPMorgan Chase holds relatively more derivatives on its balance sheet and more assets off balance sheet than the average U.S. bank, it seems reasonable to assume that the median Tier 1 Ratio is not higher in the U.S. than in Europe. The same holds, mutatis mutandis, for the other capital ratios.

3.3 Results for the U.S.

First, we will discuss the results for the U.S., since that is the focus of our study. We start by presenting some univariate statistics. This is followed by a discussion of the regression results.

[8] We apply the same risk weights used to obtain the U.S. GAAP Tier 1 Ratio to compute the IFRS-consistent Tier 1 Ratio.

3.3.1 Univariate Analysis

Figure 3.3 showed the unweighted average performance of U.S. and European banks from 2000 to 2015. We now take a closer look at the stock returns of U.S. banks by defining five quintiles based on pre-crisis stock performance, with Quintile 1 containing the 20% of banks that performed worst pre-crisis and Quintile 5 the 20% of banks that performed best. Figure 3.4 below depicts the unweighted average stock prices for banks in these five quintiles for the U.S. Table 3.4 shows the average stock performance before, during, and after the crisis per quintile.

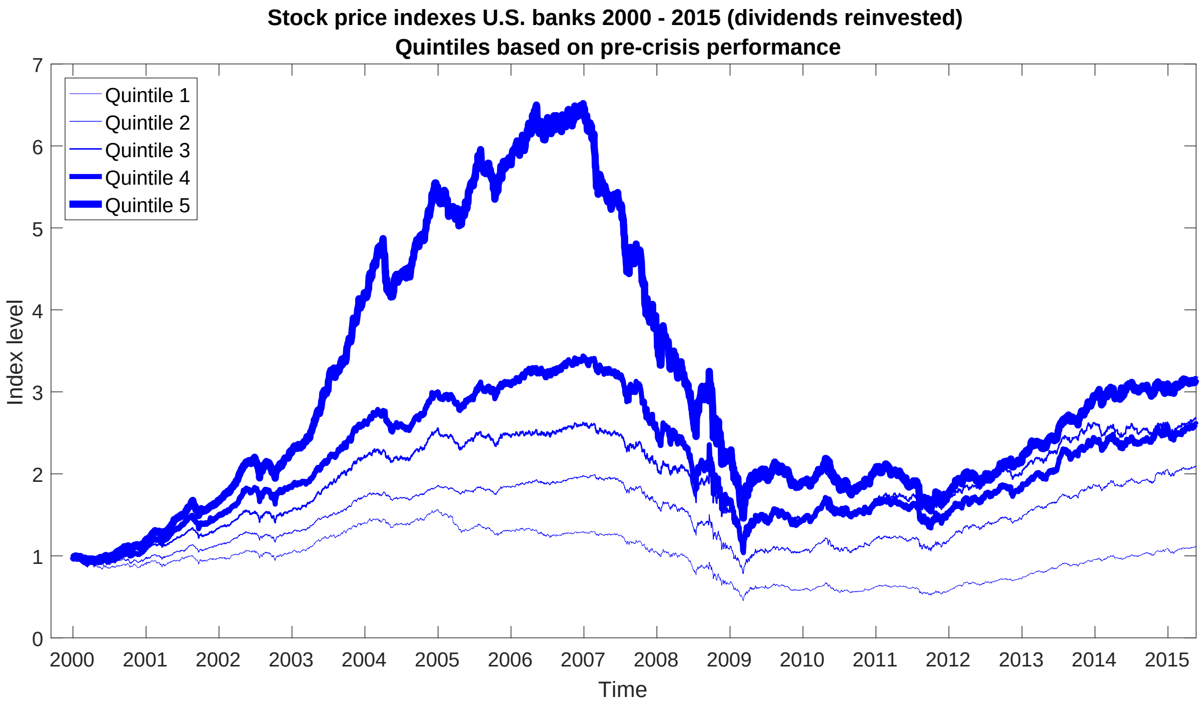

Figure 3.4. U.S. banks' unweighted average stock prices (adjusted for reinvestment of dividends and stock splits) per quintile. The first quintile (thinnest line) contains the 20% worst performers before the crisis, and the fifth quintile (thickest line) contains the 20% best performers.

Table 3.4. U.S. banks' average stock returns per quintile for different time periods. Quintiles are constructed based on pre-crisis stock performance. The first quintile contains the 20% worst performers before the crisis, and the fifth quintile contains the 20% best performers.

U.S.	Q1	Q2	Q3	Q4	Q5
2000–peak	30%	98%	162%	244%	552%
peak–2009	-65%	-60%	-57%	-70%	-78%
2009–2015	145%	167%	136%	151%	116%

The first line of the table reflects the nature of the quintiles: Quintile 1 contains the 20% worst performers before the crisis, whereas Quintile 5 contains the 20% best performers. The difference in pre-crisis performance between the quintiles is considerable, with the banks in Quintile 5 performing 18 times better on average than those in Quintile 1. During the crisis, the best performers pre-crisis, Quintiles 4 and 5, report the greatest decline, which is consistent with the findings of Fahlenbrach et al. (2012) and Beltratti and Stulz (2012). In the post-crisis period, Quintile 5 banks perform worst, whereas Quintile 2 banks perform best. These univariate results indicate that the banks that performed best pre-crisis were not only hit hardest during the crisis, but also lagged behind in the years after the crisis.

3.3.2 Multivariate Analysis

Since the extant literature has documented an impact of certain risk factors on the performance of banks (see Section 3.2.2), we now want to extend the aforementioned univariate analysis to a multivariate setting by estimating the following model:

$$Returntrough2015_i = \alpha + \beta Return2000peak_i + \gamma X_i + \varepsilon_i, \tag{3.1}$$

where i indicates a bank, $Returntrough2015$ and $Return2000peak$ are the returns after and before the crisis, respectively, and X_i are the pre-crisis bank characteristics. Our goal is to analyze how pre-crisis returns are related to post-crisis returns. Under the boom-and-bust hypothesis, a negative relationship would be expected, whereas the high risk–high reward hypothesis would imply a positive relationship. For our sample of U.S. banks, the estimation results of Equation (3.1) presented in Table 3.5 show strong support for the boom-and-bust hypothesis.

Table 3.5. Regressions of buy-and-hold post-crisis stock returns (*Returntrough2015*) on pre-crisis returns and other bank characteristics for U.S. banks. Variable definitions can be found in Appendix A. Accounting variables are measured as of December 31, 2006.

	(1)	(2)	(3)	(4)	(5)	(6)
Return2000peak	-0.1237***	-0.1208***	-0.1198**	-0.1208***	-0.2026***	-0.1206***
	(-2.69)	(-2.60)	(-2.57)	(-2.60)	(-3.12)	(-2.59)
Book-to-market	0.6871***	0.1000***		0.1004***	0.0605*	0.1007***
	(3.26)	(3.19)		(3.20)	(1.89)	(3.21)
log(Market cap)	0.2590**	0.3516***	0.3830***	0.3525***	0.4323***	0.3564***
	(2.58)	(3.66)	(4.06)	(3.67)	(4.23)	(3.70)
Beta	0.1344	-0.3385	-0.5513*	-0.3355	-0.8564**	-0.3328
	(0.36)	(-1.01)	(-1.77)	(-1.00)	(-2.44)	(-0.99)
MVLeverage	-0.0429***		0.0062***			
	(-2.82)		(2.74)			
Securities	-1.5920	-1.8270*	-1.8840*	-1.8852*	1.1522	-1.7878*
	(-1.58)	(-1.80)	(-1.85)	(-1.80)	(0.85)	(-1.76)
Funding fragility	1.2684*	1.2706*	1.3394*	1.2564*	-4.6799*	1.1843
	(1.70)	(1.68)	(1.77)	(1.65)	(-1.93)	(1.54)
Illiquidity	-0.0289	-0.0327	-0.0331	-0.0328	0.0408	-0.0318
	(-0.85)	(-0.95)	(-0.96)	(-0.95)	(0.74)	(-0.92)
BVLeverage				0.0090		
				(0.23)		
Tier 1 Ratio					-10.1118*	
					(-1.87)	
TCE Ratio						1.5732
						(0.59)
constant	0.5189	0.1869	0.1098	0.0886	0.9611	0.0331
	(0.95)	(0.35)	(0.20)	(0.13)	(1.12)	(0.06)
N	350	350	350	350	302	350
R^2	0.2592	0.2420	0.2361	0.2421	0.2967	0.2427
F	14.9122	15.5942	15.0997	13.6138	15.4488	13.6625
pvalue	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Specification 1 shows a strongly negative, and statistically highly significant, relationship between pre- and post-crisis stock returns. In the cross section of banks, a one-standard-deviation higher *Return2000peak* predicts, ceteris paribus, a 36 percentage points (–12.4% × 2.89) lower stock return from the trough to 2015. In this specification, we control for book-to-market of equity, size, beta, market value of leverage, securities to assets, funding fragility, and illiquidity of assets. This equals 21% of the sample mean return of 171% in the post-crisis period. Since Book-to-market and MVLeverage are almost perfectly correlated, with a correlation coefficient of 0.9972 and Variance Inflation Factor (VIF) of over 200, we estimate the model excluding MVLeverage in Specification 2 and Book-to-market in Specification 3. Results in Specification 2 are similar to Specification 1, while MVLeverage flips in sign between Specifications 1 and 3. These three regressions provide strong support for the boom-and-bust hypothesis and show that banks that performed well before the crisis performed badly afterwards.

Book-to-market has the expected sign, while the sign for size, log(Market cap), is opposite to expectations. High systematic risk before the crisis, as measured by Beta, is negatively associated with performance after the crisis. Moreover, we conclude that banks that were highly leveraged pre-crisis show relatively strong post-crisis returns. Banks with lower securities to assets and more nondeposit short-term debt also perform better in the post-crisis period, although these variables are not always significant, and when they are, it is only at the 10% level.

In Specifications 4 through 6, MVLeverage has been replaced by three alternative capital ratios. When it is replaced with BVLeverage (assets divided by the book value of equity), leverage is no longer significant, while we obtained similar results as in Specification 1 for the other variables.

Since depository institutions are required to report Tier 1 Ratios, we assess in Specification 3 how results change when we restrict the sample to these institutions. The main result becomes stronger than for the cross section of banks: a one-standard-deviation higher return before the crisis predicts, ceteris paribus, a 42 percentage points (–20.3% × 2.07) lower return after the crisis. Compared to the other specifications, funding fragility is now negatively related to post-crisis returns. Depository banks with more nondeposit short-term funding show relative underperformance after the crisis. Unreported regressions, in which we estimate Specifications 2 and 3 only for depository institutions, show the same strong negative correlation between pre- and post-crisis returns for depository institutions. When we restrict the estimation of Specifications 2 and 3 to non-depository institutions, the pre-crisis returns still have a negative sign but become insignificant. Taken together, these results indicate that depository institutions drive the overall negative return between pre- and post-crisis returns. Finally, following Beltratti and Stulz (2012) and Fahlenbrach et al. (2012), we include the tangible common equity ratio (TCE Ratio) in Specification 4, which does not alter our main findings.

In discussing the summary statistics, we identified outliers for the dependent and independent variables. To assess whether the above results were driven by outliers, we repeated the analysis on data which had been Winsorized at 1%. Although the significance of the pre-crisis returns drops, it remains significant at 5% in four of the specifications and at 10% (with a maximum p-value of 0.053) in the other two. For Specification 1, a one-standard-deviation higher return before the crisis is associated, ceteris paribus, with a 29 percentage points lower return after the crisis. Moreover, the negative relationships for Securities and Illiquidity become stronger, while Funding fragility is insignificant in Specifications 1 to 4 and 6.

In sum, controlling for bank characteristics, we consistently find support for the boom-and-bust hypothesis. This significant relationship still holds when we Winsorize the data at 1%, although the p-values increase slightly. The overall result seems to be mainly driven by depository institutions, as the relationship between pre- and post-crisis returns is strongest for these banks.

In order to assess how the results of our sample relate to earlier studies, most notably Beltratti and Stulz (2012) and Fahlenbrach et al. (2012), we now shift our attention to the crisis period, 2007–2009. Table 3.6 presents the estimation results of the following model:

$$Returnpeak\_trough_i = \alpha + \beta Return2000peak_i + \gamma X_i + \varepsilon_i, \tag{3.2}$$

where i indicates a bank, *Returnpeak_trough* is the return during the crisis, and the remaining variables are as previously defined.

Table 3.6. Regressions of buy-and-hold stock returns during the crisis (*Returnpeak_trough*) on pre-crisis returns and other bank characteristics for U.S. banks. Variable definitions can be found in Appendix A. Accounting variables are measured as of December 31, 2006.

	(1)	(2)	(3)	(4)	(5)	(6)
Return2000peak	-0.0095**	-0.0094**	-0.0095**	-0.0094**	-0.0155**	-0.0093**
	(-2.09)	(-2.07)	(-2.09)	(-2.16)	(-2.36)	(-2.08)
Book-to-market	0.0062	-0.0148***		-0.0155***	-0.0179***	-0.0144***
	(0.30)	(-4.82)		(-5.28)	(-5.51)	(-4.77)
log(Market cap)	-0.0200**	-0.0167*	-0.0189**	-0.0187**	0.0060	-0.0139
	(-2.02)	(-1.78)	(-2.06)	(-2.08)	(0.58)	(-1.50)
Beta	-0.1202***	-0.1371***	-0.1264***	-0.1440***	-0.1778***	-0.1337***
	(-3.26)	(-4.17)	(-4.16)	(-4.57)	(-5.00)	(-4.14)
MVLeverage	-0.0015		-0.0011***			
	(-1.02)		(-4.92)			
Securities	0.5812***	0.5728***	0.5786***	0.7063***	0.6569***	0.5956***
	(5.84)	(5.78)	(5.85)	(7.22)	(4.78)	(6.10)
Funding fragility	0.0297	0.0298	0.0303	0.0623	-0.1718	-0.0204
	(0.40)	(0.40)	(0.41)	(0.88)	(-0.70)	(-0.28)
Illiquidity	0.0014	0.0013	0.0014	0.0014	0.0004	0.0018
	(0.42)	(0.38)	(0.41)	(0.43)	(0.08)	(0.55)
BVLeverage				-0.0205***		
				(-5.66)		
Tier 1 Ratio					1.4721***	
					(2.69)	
TCE Ratio						0.9152***
						(3.58)
constant	-0.5643***	-0.5762***	-0.5680***	-0.3508***	-0.8426***	-0.6656***
	(-10.44)	(-10.92)	(-10.81)	(-5.45)	(-9.74)	(-11.56)
N	350	350	350	350	302	350
R^2	0.2103	0.2079	0.2100	0.2759	0.2905	0.2365
F	11.3480	12.8198	12.9911	16.2436	14.9993	13.2058
pvalue	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Since the period we consider as a dependent variable in these regressions largely overlaps with the period used in Table II of Fahlenbrach et al. (2012) and Table 4 of Beltratti and Stulz (2012) (both papers use the stock returns for the period from July 2007 to December 2008 as a dependent variable), we relate our results to theirs. From the first line, we can conclude that for all regressions the pre-crisis returns are negatively related to crisis returns, which is consistent with the findings of Fahlenbrach et al. and Beltratti and Stulz. Given the high correlation between MVLeverage and Book-to-market, Specification 2 excludes the former and Specification 3 excludes the latter, and we rely on both specifications in interpreting the coefficients for these two variables.

The coefficients on Book-to-market, Log(Market cap), and the capital ratios are all similar to the findings of Fahlenbrach et al. (2012): undervalued stocks perform worse, smaller banks outperform larger ones, and high pre-crisis leverage is punished during the crisis. However, the coefficient of Market Beta has the opposite sign of those findings. Although Fahlenbrach et al. consider a shorter period in computing their dependent variable and their beta is computed based on returns from 2004 to 2006 (whereas we start in 2003), the most likely reason for this difference would be the sample of banks. They consider banks with a minimum of $50m assets, while we use a minimum of $500m. Moreover, they are more restrictive in allowing a bank to be part of their sample. Furthermore, consistent with Beltratti and Stulz (2012), we found that banks with relatively more securities performed better during the crisis.[9] Unlike Beltratti and Stulz, however, Funding fragility was insignificant in our sample. Apparently, the importance of funding fragility for banks around the world (Beltratti & Stulz, 2012) does not apply to our sample of U.S. banks.

For the U.S., we have presented strong evidence that the pre-crisis stock returns of banks predict low stock performance after the crisis, controlling for book-to-market, size, beta, leverage or another capital ratio, securities, fragility of funding, and liquidity.

[9] We refer to Specification 2 in Panels A and B of Table 4 in Beltratti and Stulz (2012) since the size of the banks in those regressions is closest to the size of our banks. Nonetheless, their sample banks are much larger than ours because they consider banks with a minimum of $10bn in assets, while we consider banks with a minimum of $500m. Moreover, they consider banks from 32 different countries, while in Table 3.5 we only consider U.S. banks.

Moreover, the relationship between pre- and post-crisis returns is strongest for depository institutions. In all regressions, the coefficient of the primary explanatory variable, *Return2000peak*, was highly statistically and economically significant. The relationship we found for U.S. banks could possibly be explained by a risky business model and corporate culture that generated high pre-crisis stock returns but also prevented the banks from fundamentally restructuring post-crisis and adjusting to the harsh reality of more stringent rules and regulations and discriminating clients. In order to test whether high performers before the crisis were more risky, we relate pre-crisis stock returns to risk characteristics. We measure these characteristics at the end of 2006 (i.e., the end of the period for which we want to explain the stock returns), since this is the best reflection of the state at which a bank entered the financial crisis. We therefore estimate the following equation:

$$Return2000peak_i = \alpha + \gamma X_i + \varepsilon_i, \tag{3.3}$$

where X_i are the pre-crisis bank characteristics. The results are presented in Table 3.7.

Table 3.7. Regressions of buy-and-hold pre-crisis stock returns (*Return2000peak*) on bank characteristics for U.S. banks. Variable definitions can be found in Appendix A. Accounting variables are measured as of December 31, 2006 and loan growth is the relative increase (or decrease) in net loans between December 31, 2000 and December 31, 2006.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Book-to-market	0.1182	0.0161	0.0164	-0.2579	0.1198	0.0541	-0.0405
	(0.48)	(0.44)	(0.57)	(-0.59)	(0.48)	(0.26)	(-0.22)
log(Market cap)	-0.1125	-0.0965	0.0660	0.0963	-0.1152	-0.0080	0.1272
	(-0.95)	(-0.86)	(0.72)	(0.90)	(-0.97)	(-0.06)	(1.44)
Beta	0.1286	0.0461	-0.0073	-0.1821	0.0256		-0.6341*
	(0.29)	(0.12)	(-0.02)	(-0.46)	(0.06)		(-1.87)
MVLeverage	-0.0075			0.0206	-0.0084	-0.0034	0.0001
	(-0.42)			(0.61)	(-0.47)	(-0.21)	(0.01)
Securities	-4.2939***	-4.3319***	-3.6771***		-3.8381***	-4.1009***	-0.7334
	(-3.70)	(-3.63)	(-3.07)		(-3.38)	(-3.54)	(-0.78)
Funding fragility	2.8688***	2.8718***	-3.8051*	-5.1153**		2.9774***	-1.7607*
	(3.31)	(3.30)	(-1.76)	(-2.34)		(3.47)	(-1.80)
Illiquidity	0.0224	0.0217	0.0286	0.0480	0.0215	0.0231	0.0202
	(0.56)	(0.54)	(0.58)	(0.89)	(0.53)	(0.58)	(0.68)
BVLeverage		-0.0008					
		(-0.02)					
Tier 1 Ratio			2.4325				
			(0.50)				
Risk weights				2.6805***			
				(2.60)			
Customer deposits					-2.8912***		
					(-2.99)		
MES						29.0901	
						(0.92)	
IV						0.3996*	
						(1.82)	
Loan growth							0.9193***
							(8.14)
constant	3.2112***	3.1635***	2.2735***	-0.2678	5.5720***	2.7290***	0.7545
	(5.18)	(4.05)	(3.01)	(-0.30)	(4.86)	(4.02)	(1.54)
N	350	350	302	297	352	350	254
R^2	0.0602	0.0598	0.0717	0.0630	0.0544	0.0712	0.2687
F	3.1312	3.1049	3.2436	2.7745	2.8287	3.2693	11.2510
pvalue	0.0032	0.0035	0.0025	0.0083	0.0070	0.0013	0.0000

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Specification 1 contains the same variables we considered in previous tables.[10] In

[10] Unlike in the previous regressions, the high correlation between Book-to-market and MVLeverage has almost no influence on the estimation results. We therefore do not report separate regression results where either of them has been excluded.

Specifications 2 to 6, one of the variables from Specification 1 is replaced by an alternative indicator and, in Specification 7, we have added the loan growth from 2000 to 2006 to the variables used in Specification 1. The results presented in Table 3.7 provide support for the hypothesis that in the U.S. a risky business model was positively related to returns before the crisis. Banks with risky practices – such as having few securities and consequently high risk weights, few customer deposits and consequently high fragility in funding, and high stock return variability, as measured by idiosyncratic volatility (IV) – showed significantly higher stock returns. Capital ratios, on the other hand, are not related to pre-crisis stock returns.

The proportion of assets held in securities is negatively related to pre-crisis returns. Although in hindsight it might be surprising that banks performing worst before the crisis had relatively more securities on their balance sheet (since the crisis started with mortgage-backed securities), they were regarded as less risky by regulators at that time: their risk weights[11] were lower. This can be concluded from the negative, and highly significant, correlation of -0.6935 between Securities to Assets and Risk Weights. The flip side is that banks with more loans on the balance sheet had higher risk weights (correlation of 0.6517) and were thus viewed as more risky prior to the crisis. The results of Regression 4 are consistent with this reasoning, since higher risk weights are associated with positive pre-crisis returns.

Funding fragility is significantly positively related to pre-crisis performance in several regressions. This indicates that banks with a larger portion of short-term debt funded with sources other than customer deposits performed better before the crisis. This finding is substantiated by Specification 5, which shows that a higher level of customer deposits is negatively associated with returns. This is also in line with the finding of Demirgüç-Kunt and Huizinga (2010) that banks that “rely prominently on attracting

[11]This is a measure to gauge the overall riskiness of a bank's assets. These risk weights are used to multiply the assets in obtaining the denominator for regulatory capital ratios, such as the Tier 1 Ratio: the higher the risk weights, the riskier the assets of a bank.

nondeposit funding are very risky" (p. 626).

As an alternative for Beta, we follow Fahlenbrach et al. (2012) and simultaneously consider the marginal expected shortfall (MES) as defined in Acharya et al. (2017) and the idiosyncratic volatility (IV) of Beltratti and Stulz (2012). MES is the average stock returns of banks on the 5% of trading days from 2003 to 2006 when the S&P 500 had its lowest returns. IV represents the variability in the stock returns not explained by the market: a higher value implies greater variability after controlling for market variability. From the significantly positive relationship between IV and pre-crisis return, we again conclude that riskier banks (i.e., those with a more volatile trajectory) performed better before the crisis.

Fahlenbrach et al. (2016) have documented that banks with fast-growing loan portfolios in a three year period have lower stock returns in subsequent years than banks with slow growing loan portfolios. We wonder whether loan growth might also be a relevant factor in our analyses. In Specification 7 in Table 3.7, we have added loan growth and conclude that it is strongly positively related to pre-crisis stock returns. Furthermore, it is a relatively important characteristic as the R^2 jumps to 0.27 from a maximum of 0.07 for the other specifications. Given the strength of this relation (t-statistic of 8.14) loan growth is a candidate for explaining the negative relationship between pre- and post-crisis stock returns documented in Table 3.5. In an unreported regression we thus added loan growth to our main regression (i.e., Specification 1 in Table 3.5). We find that loan growth is significantly negatively related to post-crisis stock returns (at the 10% level) and, moreover, the negative relationship between pre- and post-crisis stock returns is no longer significant.

In sum, these results indicate that the high-performing banks from before the crisis were more risky in various respects. The strongest predictor of pre-crisis stock returns is the growth in the pre-crisis loan book. Furthermore, when we add this loan growth to our main analysis, the pre-crisis returns are no longer significantly negatively associated with post-crisis returns. This suggests that fast-growing U.S. banks drive the negative association between pre- and post-crisis stock returns.

3.3.3 Interpretation of U.S. Results

For U.S. banks, we documented a significantly negative association between returns before and after the crisis. In line with Fahlenbrach et al. (2012) and Beltratti and Stulz (2012), we also documented that banks that performed relatively well before the financial crisis performed poorly during it. We have additionally shown that the pre-crisis performance of these banks was related to a higher risk profile and stronger loan growth. In relating pre- and post-crisis returns, we controlled for factors that have been shown in previous studies to influence bank stock performance and riskiness. Hence, although some of these risk factors from before the crisis are directly related to the performance of that period, there is only one factor, pre-crisis loan growth, that seems to drive the overall negative relationship between pre- and post-crisis returns.

In this section, we discuss several interpretations of these findings. Fahlenbrach et al. (2012) have claimed that banks tend to persist in their business models and that this led them to perform badly in both the 1998 crisis and the more recent global financial crisis. Along similar lines, we argue that the business model of banks that performed badly in the recent financial crisis has not changed since. The reasons for that are different this time, however. In spite of the magnitude and impact of the 1998 crisis – Robert Rubin, then U.S. Secretary of the Treasury, stated that it was "the worst financial crisis in the last 50 years" – it did not lead to stricter banking oversight. On the contrary, one year after the crisis, the 1999 Gramm-Leach-Bliley Act [the culmination of a $300 million lobbying effort by the banking and financial services industries, according to Stiglitz (2009)] repealed the two provisions of the Glass-Steagall Act of 1932 that restricted affiliations between commercial and investment banks. In general, policy makers and regulators failed to constrain and even induced the risks taken by the financial sector (Barth et al., 2012, Chapter 4; Calomiris & Haber, 2014, pp. 224, 265–269). Since banking regulation and supervision were loosened rather than tightened in the years after that 1998 Russian financial crisis, the pre-crisis business model remained viable and the risk culture of banks flourished as never before, leading to rapid loan growth paired with low levels of capital. In the aftermath of the financial crisis of 2007–2009, however, banking regulations and oversight did change considerably, largely making successful pre-crisis business models obsolete. The pre-crisis winners were incapable of adapting their business models and risk culture to the new regulatory and economic reality and have consequently generated lagging stock returns.

We point to measures taken by the Bank for International Settlements, with Basel III, and the Financial Stability Board as examples of this increased scrutiny to enhance the safety of the financial system. In addition to these coordinated supranational actions, individual countries have imposed new laws and stricter regulation, of which the Dodd-Frank Act and the Volcker Rule are examples in the U.S.[12] One concrete measure that has received much attention in recent years is the higher liquidity and capital requirements. Baily and Elliott (2014) point to five ways in which capital regulation has become more stringent since the crisis: requirements for more capital and higher quality capital, an increase in risk weights for computing regulatory capital ratios, requirements for more capital for trading positions, and the introduction of a crude leverage ratio in which assets are unweighted. These measures constrained the banks' potential of unrestrained loan growth and forced them to become better capitalized. In addition, they have proven effective: the Financial Stability Board (2015) has documented an increase in capital, liquidity, and loss-absorbing capacity at U.S. banks. For instance, Common Equity Tier 1 Capital, the most stringent form of capital for U.S. banks, has risen from 4.6 percent of risk-weighted assets in the fourth quarter of 2007 to 11.6 percent in the third quarter of 2013 (Baily & Elliott, 2014).

[12] See `http://www.economist.com/node/21547784` for a discussion of the Dodd-Frank Act. The Volcker Rule was based on some parts of Dodd-Frank and intended to restrict commercial banks' proprietary trading activities and investments in hedge funds and private equity.

Above we have presented evidence which suggests that pre-crisis loan growth accounts for the negative association between pre- and post-crisis performance. We argue that this growth was induced by the boom in the mortgage market (e.g., Calomiris, 2009; Calomiris & Haber, 2014, Chapter 7). Although part of these mortgages were sold through securitization, the most risky banks kept large sums of high-risk mortgages on their balance sheet before the crisis (Calomiris & Haber, 2014, pp. 275–277). In addition to this direct exposure, the shadow banking system also enabled the indirect exposure to the mortgage market.[13] For instance, regular banks set up special purpose vehicles to off-load assets from their balance sheet, which enabled them to circumvent capital requirements and earn additional profits (Acharya & Schnabl, 2009; Acharya et al., 2013). These assets were securitized, and the investors in these vehicles were provided with a liquidity and credit guarantee from the regular bank to assure a high credit rating for the securities (Pozsar et al., 2010). That is, if a vehicle experienced problems with funding or had losses on its securities, the regular banks had to take the assets back onto their balance sheet. Although these securities were not regarded as risky before the crisis, at least according to their high credit ratings, they became high risks during and after the crisis (Beltratti & Stulz, 2012). After the financial crisis, when the mortgage market normalized and securitization was no longer in fashion or even allowed (Acharya & Schnabl, 2009, Figure 1; Adrian & Shin, 2009, Figure 4), possibly as a result of increased regulatory scrutiny (Financial Stability Board, 2015), this curbed the recovery of banks that depended heavily on these practices. To conclude, we note that the on-balance sheet growth in risky loans is likely to underestimate the total increase in the exposure to risky loans, that is, including the indirect exposure through the shadow banking system.

[13] Pozsar, Adrian, Ashcraft, and Boesky (2010) produced an overview of this shadow banking system that estimates it was equal to roughly \$13,000bn at the end of 2006 (cf. the size of the regular U.S. banking sector was equal to \$9,000bn in 2006 according to Pozsar et al.).

3.4 Results for Europe

Thus far, we have presented results for the U.S. banking sector, where we saw that high-performing banks from before the crisis performed worse after the crisis, thus supporting the boom-and-bust hypothesis. We will now assess whether this result also holds for Europe.

3.4.1 Univariate Analysis

In Figure 3.5, we classify banks into five quintiles according to their pre-crisis performance and draw the trajectory of these five groups from 2000 to 2015. Table 3.8 contains the corresponding numbers per quintile for the periods before, during, and after the crisis.

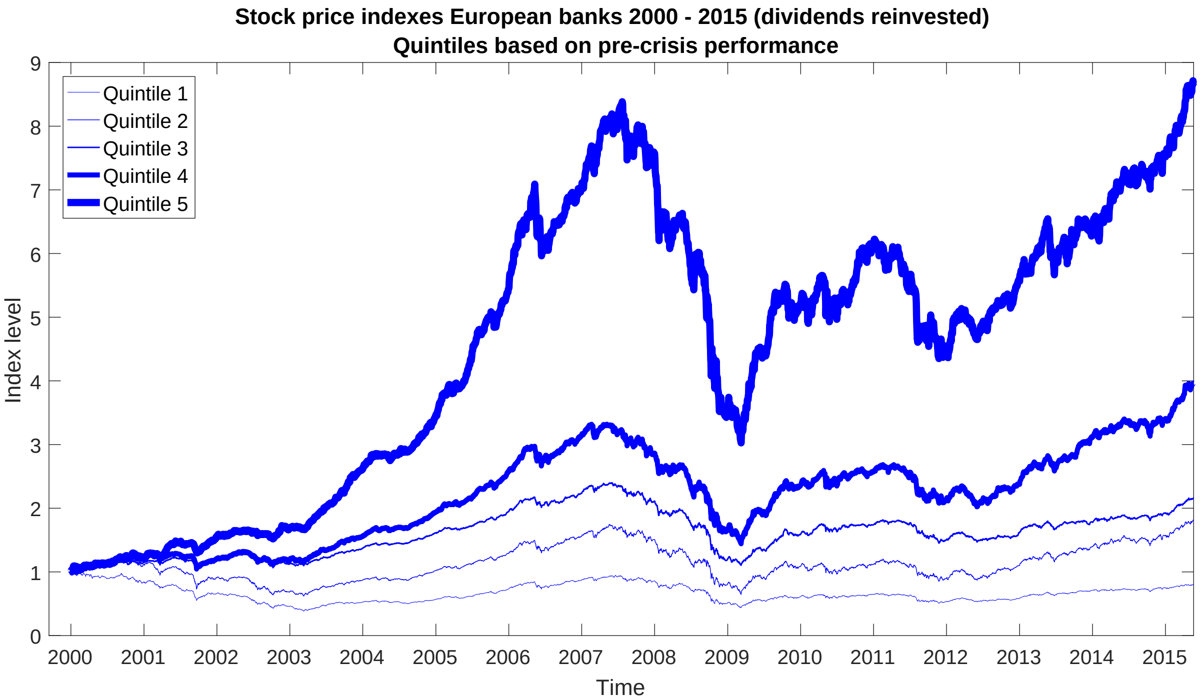

Figure 3.5. European banks' unweighted average stock prices (adjusted for reinvestment of dividends and stock splits) per quintile. The first quintile (thinnest line) contains the 20% worst performers before the crisis and the fifth quintile (thickest line) contains the 20% best performers.

Table 3.8. European banks' average stock returns per quintile for different time periods. Quintiles are constructed based on pre-crisis stock performance: the first quintile contains the 20% worst performers before the crisis, and the fifth quintile contains the 20% best performers.

Europe	Q1	Q2	Q3	Q4	Q5
2000–peak	-6.2%	73%	139%	229%	722%
peak–2009	-53%	-63%	-50%	-56%	-64%
2009–2015	97%	183%	110%	144%	197%

The first line of the table shows that in Europe the worst performers before the crisis had a negative return of -6.2%, whereas the best performers enjoyed an eight-fold increase in stock price. During the crisis, the banks in Quintile 5 experienced the greatest drop, which is in line with our findings for the U.S. However, in a striking difference with the U.S, the best-performing European banks from before the crisis continue to exhibit the best performance after the crisis, while the worst performers pre-crisis are again the worst performers after the crisis.

3.4.2 Multivariate Analysis

We now want to assess the relationship between pre- and post-crisis stock returns when we control for other bank characteristics. We therefore apply Equation (3.1) to our European sample. In contrast to the set-up for the U.S., standard errors are now clustered at the country level. The results are reported in Table 3.9.

Table 3.9. Regressions of buy-and-hold post-crisis stock returns (*Returntrough2015*) on pre-crisis returns and other bank characteristics for European banks. Variable definitions can be found in Appendix A. Accounting variables are measured as of December 31, 2006.

	(1)	(2)	(3)	(4)	(5)	(6)
Return2000peak	0.1512**	0.1359**	0.1294**	0.1365**	0.1434**	0.1359**
	(2.46)	(2.25)	(2.16)	(2.30)	(2.21)	(2.25)
Book-to-market	0.2235***	0.0262		0.0275	-0.0487	0.0253
	(3.29)	(0.29)		(0.31)	(-1.06)	(0.29)
log(Market cap)	0.0225	0.0073	-0.0126	0.0194	0.0439	0.0044
	(0.15)	(0.05)	(-0.09)	(0.13)	(0.24)	(0.03)
Beta	1.7452***	1.6514**	1.6171**	1.6702**	0.8527	1.6479**
	(3.00)	(2.79)	(2.66)	(2.83)	(0.81)	(2.75)
MVLeverage	-0.0049***		-0.0011**			
	(-5.24)		(-2.41)			
Securities	0.2071	0.0278	0.0510	0.0027	1.1709	0.0792
	(0.32)	(0.04)	(0.08)	(0.00)	(0.42)	(0.11)
Funding fragility	1.3092**	1.4834**	1.5674**	1.4465**	1.6403	1.5161*
	(2.36)	(2.29)	(2.19)	(2.22)	(0.92)	(2.09)
Illiquidity	0.0069	0.0095	0.0080	0.0088	-0.0151	0.0096
	(0.24)	(0.30)	(0.25)	(0.28)	(-0.06)	(0.31)
BVLeverage				-0.0069		
				(-0.53)		
Tier 1 Ratio					4.4133	
					(0.94)	
TCE Ratio						-0.1758
						(-0.18)
constant	-0.3111	-0.0359	0.1677	-0.0115	-0.7644	-0.0143
	(-0.27)	(-0.03)	(0.17)	(-0.01)	(-0.52)	(-0.01)
N	200	200	200	200	114	200
R^2	0.1553	0.1362	0.1384	0.1371	0.1114	0.1363
F	30.4166	4.7624	6.1559	4.8119	3.1888	4.3465
pvalue	0.0000	0.0028	0.0006	0.0021	0.0181	0.0036

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Contrary to the U.S., for Europe we find evidence suggestive of the high risk–high reward hypothesis: that is, top performers from before the crisis are again top performers after the crisis. This relationship is documented in all six specifications. From Specification 1, we conclude that, in the cross section of banks, a one-standard-deviation higher stock return before the crisis predicts a 47 percentage points (15.1% $\times$ 3.11) higher return after the crisis. This represents 28% of the mean average post-crisis stock return of 169%. Moreover, we find that banks with a larger beta and more reliance on short-term debt performed better after the crisis, which indeed suggests that higher-risk banks performed better after the crisis. Restricting the sample to depository institutions (Specification 5), we find a similar result.

The coefficient on Beta has a positive sign, which is the opposite of what we found for U.S. banks. Surprisingly, European banks with a larger exposure to the market performed better after the crisis. Securities to Assets, which was positively related to *Returnpeak2015* in the U.S., is not statistically significant for the European sample.

In order to allow for heterogeneity in the relationship between pre- and post-crisis returns for GIIPS (Greece, Ireland, Italy, Portugal, and Spain) and non-GIIPS, we interacted the pre-crisis return with a dummy which is equal to one when a bank is located in a GIIPS country and zero otherwise. In an unreported regression, we found that for non-GIIPS countries the relationship between pre- and post-crisis returns is similar to the positive relationship documented in Specification 1 of Table 3.9. For GIIPS countries, however, the association is negative but insignificant with a p-value of 0.548. We therefore conclude that our main result is driven by banks in non-GIIPS countries. Finally, we also related the performance of European banks during the crisis to performance before the crisis (unreported). The relationship is negative but insignificant in all specifications.

Hence, pre-crisis top performers recovered significantly stronger from the crisis than pre-crisis bottom performers and this relationship is driven by banks in non-GIIPS countries. This positive association between returns before and after the crisis is consistent with the high risk–high reward hypothesis and contrasts with our finding for U.S. banks. As we did for the U.S., our next step is then to relate the pre-crisis returns of European banks to risk characteristics before the crisis. We employ Equation (3.3) and cluster the standard errors at the country level. Table 3.10 contains the results.

Table 3.10. Regressions of buy-and-hold pre-crisis stock returns (*Return2000peak*) on bank characteristics for European banks. Variable definitions can be found in Appendix A. Accounting variables are measured as of December 31, 2006 and loan growth is the relative increase (or decrease) in net loans between December 31, 2000 and December 31, 2006.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Book-to-market	-0.4295**	-0.1989	-0.1349	-0.5681**	-0.4316**	-0.3800**	-0.3051
	(-2.74)	(-1.67)	(-1.65)	(-2.44)	(-2.78)	(-2.80)	(-0.68)
log(Market cap)	-0.0126	-0.0064	0.0727	-0.0660	-0.0046	-0.0242	-0.2186
	(-0.10)	(-0.05)	(0.37)	(-0.45)	(-0.04)	(-0.19)	(-1.09)
Beta	-1.6073	-1.5410	-3.1658**	-1.7059	-1.9726**		-0.9037
	(-1.70)	(-1.58)	(-2.20)	(-1.38)	(-2.16)		(-0.67)
MVLeverage	0.0058**			0.0080**	0.0057**	0.0044**	0.0016
	(2.79)			(2.17)	(2.62)	(2.29)	(0.23)
Securities	-1.9115*	-1.7033	-0.2678		-1.9069**	-1.6466*	0.6130
	(-1.99)	(-1.70)	(-0.20)		(-2.65)	(-1.97)	(0.19)
Funding fragility	1.5165	1.3688	3.4080**	3.6018**		1.3743	1.8381
	(1.42)	(1.46)	(2.28)	(2.23)		(1.25)	(0.69)
Illiquidity	0.0223	0.0202	0.3753	-0.0410	0.0264	0.0250	0.0183
	(0.81)	(0.77)	(1.55)	(-0.13)	(0.99)	(0.82)	(0.64)
BVLeverage		0.0068					
		(0.13)					
Tier 1 Ratio			11.1635				
			(1.48)				
Risk weights				4.3028			
				(1.58)			
Customer deposits					-2.0376**		
					(-2.15)		
MES						77.7426**	
						(2.24)	
IV						19.2908	
						(0.90)	
Loan growth							1.8085**
							(2.76)
constant	3.4957**	3.2004**	1.1204	0.4829	4.9068***	2.6653**	3.1499*
	(2.78)	(2.44)	(0.60)	(0.33)	(3.88)	(2.16)	(2.01)
N	200	200	114	108	211	200	47
R^2	0.1058	0.0897	0.2445	0.2556	0.1209	0.1074	0.3756
F	2.3482	1.8217	1.6193	4.7389	3.1120	2.8586	664.8555
pvalue	0.0635	0.1384	0.1901	0.0032	0.0217	0.0271	0.0000

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We observe that riskiness at European banks was rewarded before the crisis. First, high stock returns in that period were associated with high leverage. Moreover, and similar to in the U.S., banks with little securities to assets and high fragility in funding, and consequently less deposits, and high loan growth performed better before the crisis. In contrast, banks with large systematic risk performed worse as can be concluded from the negative sign of Beta and positive sign of MES. Hence, for European banks, we find some support that higher risk-taking before the crisis was associated with higher stock returns. Nonetheless, when we add these risk factors to the regression where we relate pre- to post-crisis stock returns (see Table 3.9), we still find a significant positive relationship.

3.4.3 Discussion: U.S. Versus Europe

Contrary to the U.S., for Europe we find that the high-performing banks from before the crisis are also the high-performing banks after the crisis. How can that be explained? For the U.S., we argued that the banks' participation in the mortgage bubble, directly through a growing loan portfolio and indirectly through the shadow banking system, explains the negative relationship between pre- and post-crisis stock returns. The benefits reaped before the crisis were no longer available after the crisis as a result of the implosion of the mortgage market and increased regulation, which forced these banks to adjust their risky business model. In this section, we explore the importance of these factors for European banks.

First, Barth et al. (2012, Chapter 5) document that the mortgage market of some European countries, such as Ireland, Spain, and the United Kingdom, also experienced a boom before the financial crisis. The positive relationship we found between pre-crisis stock returns and loan growth before the crisis is consistent with this conjecture. Subsequently, in an unreported regression we also added loan growth to the main specification relating pre- and post-crisis stock returns (i.e., Specification 1 of Table 3.9). Although we found that pre-crisis loan growth is significantly negatively related to stock returns after the crisis, it does not alter the significant positive association between pre- and post-crisis returns. In sum, fast-growing European banks had relatively high pre-crisis and relatively low post-crisis stock returns. Nonetheless, this does not alter the positive relationship between performance before and after the crisis.

Next, we assess whether European banks were exposed to unobservable risks through the European shadow banking market. We start with comparing the sizes of the European and U.S. securitization markets. The European securitization market was much smaller than the U.S. market, peaking at around €2,000bn versus a peak in the U.S. at around $11,000bn (Bank of England and European Central Bank, 2014). Moreover, the incidence of default on these securities was much lower in Europe than in the U.S. (Bank of England and European Central Bank, 2014). Therefore, we conclude that it is unlikely that European banks had large exposures to the European shadow banking market. Moreover, when they did have a large exposure, the low rate of default restricted the damage. Hence, the riskiness of the local shadow banking market was considerably larger in the U.S. than in Europe.

Even though the European shadow banking system was relatively small and stable, a significant exposure of European banks to the U.S. shadow system might have exposed them to similar problems as U.S. banks. Pozsar et al. (2010) and Acharya et al. (2013) have indeed documented such exposure on the part of European banks, but this typically pertained to the larger financial institutions.[14] Moreover, the involvement of these large European banks in the securitization process was smaller (Pozsar et al., 2010). A possible explanation for the smaller exposure of European banks relative to their U.S. counterparts might be differences in the way various accounting systems treated assets that were kept off balance sheet. The Bank of England and European Central Bank (2014) have stated that the U.S. GAAP accounting system was better suited to off-loading assets by means of structured finance vehicles than the systems applied in Europe (i.e., IFRS or national GAAP).

[14] Some relatively small German banks form an exception. The exposed banks had large holdings of U.S. securities (see `http://www.economist.com/news/finance-and-economics/21638143-seven-german-landesbanken-survived-financial-crisis-are-still` and Claessens, DellAriccia, Igan, and Laeven, 2010).

The positive association between pre- and post-crisis performance does not disappear after we control for observable risk factors. Moreover, the exposure of European banks to the U.S. and European shadow banking systems was only limited. Consequently, other non-observable factors – that is, factors that are beneficial to bank performance and did not need to change after the crisis, such as client focus, strong corporate culture, and quality of management – might explain the positive relationship between pre- and post-crisis bank performance. If so, the positive association between pre- and post-crisis performance should merely be regarded as a sign of bank strength and not a reflection of high risk practices.

3.5 Robustness Checks

In this section, we investigate the robustness of the U.S. results when we apply estimation techniques to deal with outliers, treat delisted banks differently, use alternative pre-crisis periods, and focus on different size categories.

3.5.1 Robust Regression

The objectives with robust estimators are to 1) simultaneously maintain a reasonably high level of efficiency when outliers are absent; 2) remain stable (perform not much worse) when there are a few outliers; and 3) not break down when there are numerous outliers (Huber & Ronchetti, 2009). Efficiency in our regression context means a relatively low standard deviation of the regression coefficients. Three types of outliers are typically identified (e.g., Rousseeuw & Leroy, 2003): vertical outliers, good leverage points, and bad leverage points. Vertical outliers are observations that are only outliers in the direction of the dependent variable (y-direction) but not the independent variables (x-direction). These outliers pull the regression line towards them and can therefore distort the estimation. Good leverage points are outliers in both the x- and y-directions. Since they lie close to the regression line, they have no impact on the parameter estimates. Bad leverage points are outlying in the x-direction but not in the y-direction and hence are not close to the regression line. As the names indicate, good leverage points are less of a problem than bad leverage points, which distort estimation.

Huber (1964) proposed a generalization to minimize squared residuals and introduced the M-estimator. The objective is not necessarily to minimize the quadratic error terms, but to minimize any function. This estimator is referred to as the M-estimator because this class contains the sample mean, the median, and all the maximum likelihood estimators. Although these estimators are able to deal with vertical outliers, they are unable to cope with bad leverage points. In other words, they break down when only a few outliers contaminate the data. Therefore, an alternative class of S-estimators was introduced by Rousseeuw and Yohai (1984), with which a high breakdown point could be achieved, meaning that the estimator can handle a relatively large number of outliers before derailing. The latter class of estimators, however, suffers from a low level of efficiency when there are no outliers. Finally, Yohai (1987) developed the MM-estimator, which has a high breakdown point, while simultaneously enjoying high efficiency. Although this might seem like the best of both worlds, Huber and Ronchetti (2009) criticize estimators with a high breakdown point for not being stable; that is, a small number of outliers might distort the efficiency of the model.

The aforementioned discussion only lists a few of the large number of available robust estimators[15] and indicates that there is no consensus as to which estimator is the preferred one under which conditions. We therefore list the results for our main regressions using OLS, Winsorizing at 1%, the M-estimator, and the MM-estimator. We follow Verardi and Croux (2009) in choosing the `rreg` command in Stata for our M-estimator and an efficiency of 70% for our MM-estimator. Results are presented in Tables 3.11 and 3.12.

[15] See, e.g., Huber and Ronchetti (2009, pg. 195).

Table 3.11. Regressions of buy-and-hold post-crisis (*Returntrough2015*) stock returns on pre-crisis returns and other bank characteristics. In Specifications 1 to 3, we use OLS; and in Specifications 4 to 6, we Winsorize the data at 1%. Variable definitions can be found in Appendix A. Accounting variables are measured as of December 31, 2006.

	OLS			Winsorizing		
	(1)	(2)	(3)	(4)	(5)	(6)
Return2000peak	-0.1237***	-0.1208***	-0.1198**	-0.1577**	-0.1483*	-0.1714**
	(-2.69)	(-2.60)	(-2.57)	(-2.07)	(-1.95)	(-2.28)
Book-to-market	0.6871***	0.1000***		0.8881	1.9695***	
	(3.26)	(3.19)		(1.08)	(3.71)	
log(Market cap)	0.2590**	0.3516***	0.3830***	0.4389***	0.4220***	0.4219***
	(2.58)	(3.66)	(4.06)	(3.92)	(3.77)	(3.81)
Beta	0.1344	-0.3385	-0.5513*	-0.3385	-0.3123	-0.3225
	(0.36)	(-1.01)	(-1.77)	(-0.81)	(-0.75)	(-0.77)
MVLeverage	-0.0429***		0.0062***	0.0734*		0.1084***
	(-2.82)		(2.74)	(1.73)		(3.95)
Securities	-1.5920	-1.8270*	-1.8840*	-2.5125**	-2.1902**	-2.6240**
	(-1.58)	(-1.80)	(-1.85)	(-2.38)	(-2.10)	(-2.50)
Funding fragility	1.2684*	1.2706*	1.3394*	1.0074	1.1011	0.9682
	(1.70)	(1.68)	(1.77)	(1.33)	(1.45)	(1.28)
Illiquidity	-0.0289	-0.0327	-0.0331	-0.0830*	-0.0750	-0.0812*
	(-0.85)	(-0.95)	(-0.96)	(-1.78)	(-1.61)	(-1.74)
constant	0.5189	0.1869	0.1098	-1.1399	-1.1152	-0.7936
	(0.95)	(0.35)	(0.20)	(-1.47)	(-1.43)	(-1.12)
N	350	350	350	350	350	350
R^2	0.2592	0.2420	0.2361	0.1143	0.1066	0.1113
F	14.9122	15.5942	15.0997	5.5035	5.8270	6.1184
pvalue	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.12. Regressions of buy-and-hold post-crisis (*Returntrough2015*) stock returns on pre-crisis returns and other bank characteristics. In Specifications 7 to 9, we use the M-estimator (`rreg` command in Stata), and in Specifications 10 to 12, the MM-estimator. Variable definitions can be found in Appendix A. Accounting variables are measured as of December 31, 2006.

	M			MM		
	(7)	(8)	(9)	(10)	(11)	(12)
Return2000peak	-0.0872***	-0.0871***	-0.0869***	-0.2065***	-0.2067***	-0.1931***
	(-2.65)	(-2.66)	(-2.65)	(-6.64)	(-6.68)	(-5.94)
Book-to-market	-0.0848	-0.0395		-0.8883	-0.9859**	
	(-0.23)	(-0.70)		(-1.53)	(-2.54)	
log(Market cap)	0.2496***	0.2492***	0.2492***	0.3026***	0.3052***	0.3130***
	(3.40)	(3.40)	(3.40)	(3.64)	(3.76)	(3.70)
Beta	-0.7357***	-0.7324***	-0.7297***	-1.0691***	-1.0843***	-0.9496***
	(-2.63)	(-2.63)	(-2.62)	(-3.65)	(-3.94)	(-3.28)
MVLeverage	0.0025		-0.0022	-0.0054		-0.0284***
	(0.12)		(-0.69)	(-0.31)		(-2.83)
Securities	0.6280	0.6386	0.6524	1.9771***	1.9755***	1.9055***
	(0.87)	(0.89)	(0.91)	(3.13)	(3.17)	(2.77)
Funding fragility	1.4551***	1.4550***	1.4505***	1.6528**	1.6526**	1.5984**
	(2.71)	(2.72)	(2.71)	(2.04)	(2.06)	(1.97)
Illiquidity	-0.0211	-0.0211	-0.0210	-0.0076	-0.0081	-0.0112
	(-0.87)	(-0.87)	(-0.86)	(-0.41)	(-0.46)	(-0.60)
constant	0.0222	0.0164	0.0078	0.0326	0.0344	-0.3863
	(0.05)	(0.04)	(0.02)	(0.05)	(0.06)	(-0.69)
N	349	349	349	350	350	350
R^2	0.1053	0.1052	0.1048			
F	5.0016	5.7243	5.7007			
pvalue	0.0000	0.0000	0.0000			

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

First we note that in all 12 specifications, pre-crisis returns remain strongly negatively related to post-crisis returns . Specifications 1, 4, 7, and 10 are the baseline regressions. Due to the high pairwise correlation between MVLeverage and Book-to-market, we exclude one of these in the other specifications; in interpreting the results for the Book-to-market and MVLeverage variables, we rely on Specifications 2 and 3. Whereas significance is comparable when using OLS and the M-estimator, it drops when we Winsorize the data and increases considerably when we use the MM-estimator. Applying the MM-estimator, we find that in the cross section of banks, a one-standard-deviation higher pre-crisis return predicts a 60 percentage points (–20.7% $\times$ 2.89) lower return after the crisis. This represents a 24 percentage points larger decrease compared to OLS.

Comparing the other independent variables, we note that OLS and Winsorizing yield similar results. However, the M- and MM-estimators do differ for some of the variables. Although Beta had a negative relationship (not always significant) for OLS and Winsorizing, it becomes highly negatively significant when using the M- and MM-estimators. Hence, banks with high systematic risk before the crisis show a significantly lower performance in the recovery period. Furthermore, three variables – Book-to-market, MVLeverage, and Securities – change signs and become significant, at least at the 5% level, with the MM-estimator. In particular, the highly significant negative sign of MVLeverage is interesting. When using the MM-estimator, pre-crisis leverage, which is one of the most prominent risk factors for banks, turns out to be a predictor of post-crisis returns.

Taken all together, though, the negative relationship between pre- and post-crisis returns remains unchanged when three robust regression alternatives are applied. That strongly indicates the robustness of our main result. We also performed these robust regression methods for Europe (unreported). Applying Winsorizing and the M-estimator raised the positive significant relationship between pre- and post-crisis returns, with the p-value decreasing from 5% to 1%. However, with the MM-estimator, the p-value increases to 10%. Hence, for Europe, we also conclude that our main result is consistent for all specifications.

3.5.2 Delisted Banks

In the main text, we dealt with delisted banks by setting their return equal to zero after the last day their stock price was recorded in Datastream. In this subsection, we explore two alternative ways of handling the returns of delisted banks. First, we drop delisted banks from the sample altogether, and second, we extend the stock returns of delisted banks with the S&P 500 Financials index as of the moment at which stock data is no longer available. This latter method was proposed by Fahlenbrach et al. (2012). Table 3.13 contains the results.

Table 3.13. Regressions of buy-and-hold post-crisis (*Returntrough2015*) stock returns on pre-crisis returns and other bank characteristics. In Specifications 1 to 3, we exclude delisted banks; and in Specifications 4 to 6, the returns of delisted banks are set equal to the returns of the S&P 500 Financials index as of the moment of delisting. Variable definitions can be found in Appendix A. Accounting variables are measured as of December 31, 2006.

	Drop delisted banks			Extend returns		
	(1)	(2)	(3)	(4)	(5)	(6)
Return2000peak	-0.1117**	-0.1105**	-0.1097**	-0.1289***	-0.1260**	-0.1251**
	(-2.13)	(-2.11)	(-2.10)	(-2.64)	(-2.56)	(-2.54)
Book-to-market	0.4858	0.1923***		0.6703***	0.0987***	
	(0.73)	(4.45)		(3.00)	(2.98)	
log(Market cap)	0.2587**	0.2549**	0.2552**	0.2045*	0.2946***	0.3255***
	(2.21)	(2.18)	(2.18)	(1.92)	(2.90)	(3.26)
Beta	0.6357	0.6797	0.6869	0.1449	-0.3156	-0.5240
	(1.33)	(1.45)	(1.45)	(0.37)	(-0.89)	(-1.59)
MVLeverage	-0.0236		0.0153***	-0.0418**		0.0062**
	(-0.44)		(4.41)	(-2.59)		(2.56)
Securities	-3.3155**	-3.4152***	-3.4837***	-1.5558	-1.7846*	-1.8406*
	(-2.58)	(-2.70)	(-2.75)	(-1.46)	(-1.66)	(-1.71)
Funding fragility	1.1995	1.1635	1.1473	1.2909	1.2929	1.3601*
	(1.40)	(1.37)	(1.35)	(1.63)	(1.62)	(1.70)
Illiquidity	-0.0236	-0.0236	-0.0235	-0.0222	-0.0259	-0.0263
	(-0.60)	(-0.60)	(-0.60)	(-0.61)	(-0.71)	(-0.72)
constant	0.9362	0.9250	0.9120	1.0716*	0.7484	0.6725
	(1.43)	(1.42)	(1.40)	(1.85)	(1.31)	(1.18)
N	239	239	239	350	350	350
R^2	0.3293	0.3287	0.3278	0.2246	0.2094	0.2041
F	14.1171	16.1617	16.0890	12.3449	12.9385	12.5308
pvalue	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The main result of the chapter – that is, that a significant negative relationship exists between pre- and post-crisis stock returns for U.S. banks – still holds at the 5% level of significance. In the first three specifications, delisted banks have been excluded from the sample and the significance drops only slightly compared to the results reported in Table 3.5. In Specifications 2 and 3, MVLeverage and Book-to-market are excluded from the sample to account for the high correlation between these variables. Extending the returns as of delisting with returns from the S&P 500 Financials index also leaves the main results unchanged. We can therefore conclude that our main results were not impacted by the way we treated delisted banks.

3.5.3 Start of the Pre-crisis Period

Until now we have used January 1, 2000 as starting point to compute the pre-crisis stock returns. Since this date is chosen rather arbitrarily, in this section, we check for the robustness of our results when we use two alternative starting points, that is, January 1, 2002 and January 1, 2004. First, in Figure 3.6 we draw graphs for the unweighted average stock prices per quintile for both starting moments.[16]

[16] In this section, we exclude one bank from the sample. Its stock price was equal to 0.20 at the start of 2002 and 0.02 at the start of 2004 while its maximum equaled 28.21 over the period from 2000 to 2015. Relative to 0.02 the maximum is 1411 times larger. In addition to these enormous returns, the stock price of this bank can change materially from one day to another, which would distort the graphs of Figure 3.6. Furthermore, the bank's low stock prices at the start of 2002 and 2004 imply enormous pre-crisis returns, that is, 8000% and 81150%, respectively. Since the bank's post-crisis stock return is also an outlier with 2352%, this observation distorts the regression results. Therefore, we exclude it in this section. We note that this bank did not cause this problem in the main text because its stock price was equal to 2.64 on January 1, 2000.

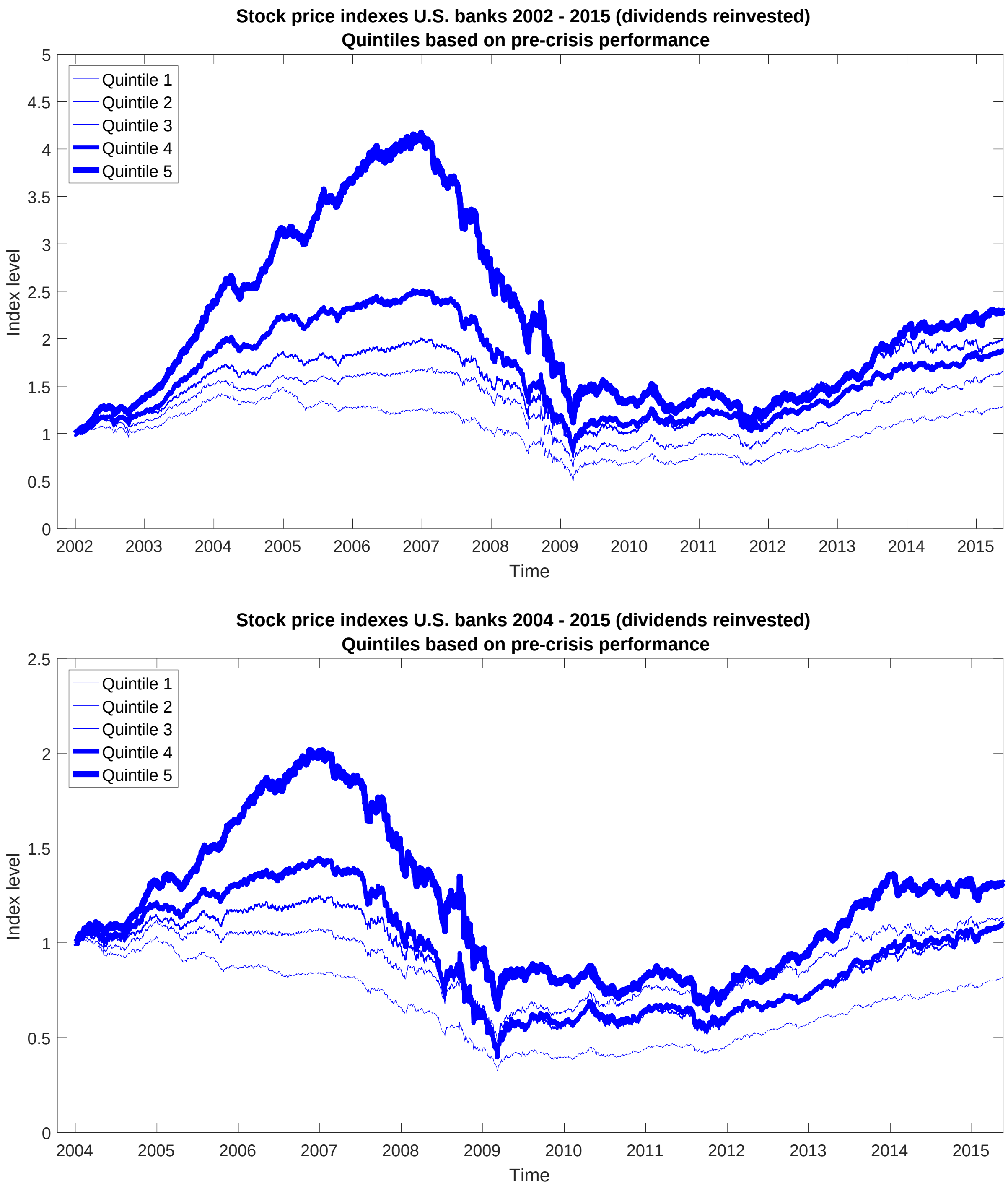

Figure 3.6. U.S. banks' unweighted average stock prices (adjusted for reinvestment of dividends and stock splits) per quintile. The starting dates in the top and bottom panel are January 1, 2002 and January 1, 2004, respectively. The first quintile (thinnest line) contains the 20% worst performers before the crisis, and the fifth quintile (thickest line) contains the 20% best performers.

We conclude that the course of the lines in both the top and bottom figure is largely similar to the course of the lines in Figure 3.4. Next, in Table 3.14, we present our results for our main regressions when we apply the alternative starting times.

Table 3.14. Regressions of buy-and-hold post-crisis (*Returntrough2015*) stock returns on pre-crisis returns and other bank characteristics. In Specifications 1 to 3, we use January 1, 2002 as starting point for our main independent variable; and in Specifications 4 to 6, we use January 1, 2004 as starting point. Variable definitions can be found in Appendix A. Accounting variables are measured as of December 31, 2006.

	Start 1-1-2002			Start 1-1-2004		
	(1)	(2)	(3)	(4)	(5)	(6)
Return2002peak	-0.3581***	-0.3666***	-0.3674***			
	(-3.43)	(-3.47)	(-3.48)			
Return2004peak				-0.9796***	-1.0208***	-1.0172***
				(-3.32)	(-3.42)	(-3.41)
Book-to-market	1.5665***	-0.0009		1.5460***	0.0109	
	(3.06)	(-0.01)		(3.01)	(0.14)	
log(Market cap)	0.3157***	0.3147***	0.3052***	0.3688***	0.3701***	0.3605***
	(3.11)	(3.06)	(2.97)	(3.59)	(3.56)	(3.47)
Beta	-0.2486	-0.2198	-0.1894	-0.2681	-0.2433	-0.2122
	(-0.64)	(-0.56)	(-0.48)	(-0.69)	(-0.62)	(-0.54)
MVLeverage	-0.0886***		-0.0021	-0.0868***		-0.0014
	(-3.09)		(-0.47)	(-3.02)		(-0.32)
Securities	-1.6905*	-2.0462**	-2.0348**	-1.4741	-1.8276*	-1.8151*
	(-1.68)	(-2.02)	(-2.01)	(-1.48)	(-1.83)	(-1.81)
Funding fragility	1.2711*	1.0910	1.1046	1.3688*	1.2007	1.2111
	(1.73)	(1.47)	(1.49)	(1.85)	(1.61)	(1.62)
Illiquidity	-0.0341	-0.0380	-0.0375	-0.0508	-0.0554	-0.0549
	(-1.01)	(-1.12)	(-1.10)	(-1.48)	(-1.60)	(-1.58)
constant	0.5097	0.7200	0.7800	0.0245	0.2226	0.2809
	(0.88)	(1.24)	(1.35)	(0.04)	(0.41)	(0.52)
N	349	349	349	349	349	349
R^2	0.1206	0.0958	0.0964	0.1187	0.0950	0.0952
F	5.8273	5.1635	5.1990	5.7236	5.1124	5.1251
pvalue	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Comparing these results to our main results which we presented in Table 3.5, we conclude that the negative association between pre- and post-crisis stock returns becomes stronger when we use two alternative starting points for the pre-crisis period.

3.5.4 Does Size Matter?

One aspect of banks that has been much disputed since the financial crisis is the importance of their size. Do large banks have specific characteristics – such as, for example, higher levels of complexity and bureaucracy, a greater lack of transparency, and more agency conflicts – that make them more vulnerable to various kinds of risk? We therefore split our sample according to 1) the median total assets at the end of 2006 and 2) the size of assets, using $50bn as the dividing line (the Dodd-Frank Wall Street Reform and Consumer Protection Act used this threshold of $50bn assets as a measure of systemic importance).

Table 3.15. Regressions of buy-and-hold post-crisis stock returns (*Returntrough2015*) on pre-crisis returns and other bank characteristics for U.S. banks and different size categories. Variable definitions can be found in Appendix A. Accounting variables are measured as of December 31, 2006.

	Largest 50% (1)	Smallest 50% (2)	>$50bn (3)	<$50bn (4)
Return2000peak	-0.0879	-0.2023**	-2.0319*	-0.0883**
	(-1.42)	(-2.44)	(-2.00)	(-1.99)
Book-to-market	1.9494***	-0.5850	6.8666	0.8844***
	(2.75)	(-0.81)	(1.24)	(4.07)
log(Market cap)	0.4328***	-0.4098	-0.2567	-0.1120
	(3.01)	(-1.27)	(-0.31)	(-0.75)
Beta	0.0955	-0.2140	-3.1573	0.6658
	(0.14)	(-0.38)	(-1.15)	(1.62)
MVLeverage	-0.1100***	0.0537	-0.5446	-0.0557***
	(-2.78)	(0.94)	(-1.36)	(-3.60)
Securities	-3.2174*	0.3195	-4.1665	-1.1815
	(-1.96)	(0.30)	(-0.85)	(-1.09)
Funding fragility	1.2285	2.1871	9.2484**	1.0552
	(1.22)	(1.32)	(2.12)	(1.30)
Illiquidity	-0.0515	-0.0324	0.0892	-0.0123
	(-1.11)	(-0.53)	(0.21)	(-0.36)
constant	-0.5120	3.3358**	11.6414	2.1026***
	(-0.48)	(2.16)	(1.17)	(2.79)
N	176	174	27	323
R^2	0.1596	0.5488	0.3310	0.2590
F	3.9631	25.0820	1.1130	13.7156
pvalue	0.0003	0.0000	0.3999	0.0000

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The relationship between returns before and after the crisis is significantly negative for the smallest 50% of banks (Specification 2). A one-standard-deviation higher pre-crisis return for this group is associated with a 35 percentage points lower return after the crisis. For the largest 50% of banks, the relationship is insignificant, with a p-value of almost 16%. In Specifications 3 and 4, we divide the sample into very large banks (more than \$50bn in assets) and the rest, respectively. We find a significant relationship for both groups. In the cross section of very large banks, a one-standard-deviation higher return before the crisis implies a 178 percentage points lower post-crisis return, which amounts to 44% of the mean return of these banks after the crisis. However, given the limited sample size of 27 large banks and the inability of rejecting the hypothesis that all parameter coefficients equal zero (the F-test has a p-value of 0.40), we have to be careful in drawing firm conclusions from this.

We conclude that the overall negative relationship before and after the crisis is driven by the smallest 50% of banks and the very large banks. In an unreported regression, where we focused on the remaining banks – that is, banks in the upper half of the size distribution with less than \$50bn in assets – we found no significant relationship between pre- and post-crisis returns.

3.6 Summary and Conclusion

We present new, strong evidence that U.S. banks that performed well before the financial crisis have been unable to recover since because they became bottom performers in the aftermath of the crisis: high pre-crisis stock returns for U.S. banks predict low post-crisis stock returns. Moreover, and consistent with earlier studies, we report that pre-crisis high-performing U.S. banks were bottom performers *during* the crisis. These results were not driven by size, type (i.e., investment banks), delistings, or outliers. For European banks, on the other hand, we found a positive relationship between pre- and post-crisis stock returns.

High pre-crisis stock returns of U.S. banks were associated with a number of pre-crisis risk characteristics, notably fragility in funding, a higher variability in stock returns, and loan growth. This result also holds for European banks, where also high leverage was positively related with pre-crisis stock returns.

For the U.S., the boom-and-bust hypothesis is strongly supported by our findings. The analysis indicates that high pre-crisis stock returns were caused by risky business model characteristics, which seems to be best captured by significant pre-crisis loan growth. Their low stock returns during the crisis were the negative result of that same risky business model. We argue that the subsequent underperformance of these previously high-performing banks in the first six years after the crisis has been due to the tightening of banking regulations and curbing of risky bank practices that have largely made the high-risk, high-performing business model from before the crisis obsolete. Apparently, the risky business model and practices of pre-crisis high-performing banks were so deeply engrained in their culture and behavioral and organizational DNA that they were unable to expeditiously embrace and adopt a new, more client centric, and trust-based business model. European pre-crisis high-performing banks continued to systematically outperform after the crisis. Unlike their U.S. counterparts, these banks experienced less trouble in adjusting to the post-crisis environment.

Appendix

A. Variable Definitions

- *Assets* - We use the $ book value of assets for U.S. banks and the € book value for European banks (in millions).

- *Beta* - Beta of CAPM is used as a proxy for systematic risk. For American companies, we estimate a CAPM of weekly returns in excess of the three-month T-bill from January 1, 2003, to December 31, 2006. The market is represented by the S&P 500 index. For European banks, we use the euro interbank lending rate for three months (i.e., Euribor) as the short rate and the STOXX 600 as the index. We estimate the following time series regression:

$$R_{i,t} - r_{0,t} = \alpha_i + \beta_i \left(R_{M,t} - r_{0,t}\right) + \varepsilon_{i,t}, \tag{3.4}$$

where $R_{i,t}$ is the return of company i in week t, $r_{0,t}$ the short rate, and $R_{M,t}$ the market return. β_i is the exposure to systematic risk of company i and the variable in question.

- *Book-to-market* - Book value of common equity to market value of common equity.
- *BVLeverage* - The book value of assets to book value of equity. The book value of equity is the sum of equity and preferred shares and hybrid capital accounted for as equity.
- *Customer deposits to assets* - Customer deposits to total assets.
- *Funding fragility* - Deposits from other banks, other deposits, and short-term borrowings, and repurchase agreements and cash collateral normalized by total deposits (customers and companies), money market funds, and short-term funding.
- *Illiquidity* - Deposits from other banks, other deposits, and short-term borrowings, and repurchase agreements and cash collateral normalized by liquid assets.
- *IV* - Idiosyncratic volatility defined as

$$IV_i = \sqrt{\mathrm{Var}\left(e_{i,t}\right)}, \tag{3.5}$$

  where $e_{i,t}$ is the residual for company i at time t from the CAPM regression [see regression Equation (3.4)].

- *Loans* - Net loans to assets. Net loans equals gross loans minus the reserves for impaired or non-performing loans.
- *Loan growth* - The relative increase (or decrease) in net loans between December 31, 2000 and December 31, 2006.
- *Market capitalization* - The market value of equity in \$ millions for U.S. banks and € millions for European banks. The maximum for Datastream's Market Value (MV) and Market Value for Company (MVC) variables is used. For companies with a single listed equity security, these numbers are equal. For companies with

more than one listed equity security or unlisted equity securities, the latter is the sum of these, while the former ignores them.

- *MES* - Marginal Expected Shortfall from Acharya et al. (2017). The average return of company i during the 5% worst daily market returns between January 1, 2003, and December 31, 2006:

$$MES_{i,5\%} = \frac{1}{\#days} \sum_{\text{t: market return is in 5\% tail}} R_{i,t}, \tag{3.6}$$

where $R_{i,t}$ is the return of company i during day t.

- *MVLeverage* - The book value of assets minus the book value of equity (see *BVLeverage* for definition) plus the *Market capitalization* normalized by *Market capitalization*.

- *Return2000peak* - Buy-and-hold stock returns, with reinvested dividends and adjusted for stock splits, from January 1, 2000, to the pre-crisis peak. The peak is defined as the highest level of the unweighted average of buy-and-hold stock returns for our sample banks before the start of the crisis. In the U.S., the peak was reached on December 28, 2006, and in Europe, on July 19, 2007.

- *Returnpeak_trough* - Buy-and-hold stock returns, with reinvested dividends and adjusted for stock splits, from the peak to the trough. The peak is defined as the highest level of the unweighted average of buy-and-hold stock returns for our sample banks before the start of the crisis. In the U.S., the peak was reached on December 28, 2006, and in Europe, on July 19, 2007. The trough is the lowest level of the unweighted average of buy-and-hold stock returns for our sample banks after the start of the crisis. This date, March 9, 2009, coincides for U.S. and European banks.

- *Returntrough2015* - Buy-and-hold stock returns, with reinvested dividends and adjusted for stock splits, from the trough to May 22, 2015. The trough is the lowest level of the unweighted average of buy-and-hold stock returns for our sample banks after the start of the crisis. This date, March 9, 2009, coincides for U.S. and European banks. The returns for banks delisted after the start of the crisis are set equal to zero as of the moment their stock price is no longer available in Datastream.

- *Risk weight* - The bank's risk weight according to the Basel rules and computed as the risk-weighted assets to assets. For banks for which risk-weighted assets are not available, we can sometimes use:

$$\frac{\frac{\text{Tier 1 Capital}}{\text{Tier 1 Ratio}}}{\text{Assets}} = \frac{\text{Risk-weighted assets}}{\text{Assets}}.$$

- *Securities* - Securities held on the balance sheet to total assets. The securities category is comprised of reverse repurchase agreements, cash collateral, trading securities, derivatives, available for sale securities, held to maturity securities, at-equity investments, and other securities.

- *TCE Ratio* - Tangible common equity to tangible assets. Goodwill and other intangibles are subtracted from common equity to obtain the numerator and from assets to obtain the denominator.

- *Tier 1 Ratio* - The ratio of Tier 1 Capital to risk-weighted assets.

B. Manual Data Adjustments

Certain firms had a stock price (Return Index in Datastream) equal to zero. However, in some cases, the stock price then grew larger than zero. Since the stock returns would otherwise be equal to infinity for stocks that recover to values greater than zero, the zeros have been replaced with the first non-zero stock price after the zeros. So if a stock price is non-zero at $t = 0$ and $t = 2$ and equal to zero at $t = 1$, the price of $t = 2$ is used as the price at $t = 1$. This occurred in ten cases in our dataset.

4 | There's a New Sheriff in Town: The Case of a Cooperative Bank

Co-Authors: Kees Cools, Hans Groeneveld, and Arthur van Soest

Abstract

How does CEO turnover impact bank performance? To answer this question, we use a panel data set with information on 106 banks over a 5-year period (2010–2015). This sample provides a unique setting for testing whether and how CEO turnover matters for bank performance by balancing homogeneity (all banks were part of a single European cooperative) and heterogeneity (the decision freedom of bank CEOs). We present strong evidence that the return on assets significantly declines in the first year(s) after a CEO change. Economically, the effect is large, with declines of 0.08 percentage points in the first year and 0.17 percentage points in the first two years, amounting to 23% and 50% of the standard deviation in return on assets, respectively. The decline in performance is caused almost entirely by an increase in provisions for impaired loans. The evidence points to two underlying motives for this increase: 1) to offset a backlog in provisions on the part of the old CEO and 2) to ensure a position from which to boost results in the future through a subsequent decrease in provisions.

4.1 Introduction

We investigate how the performance of a cooperative bank is influenced by a change in CEO. Research on the impact of CEOs on firm policies and performance has increased in recent years. Bertrand and Schoar (2003) have highlighted the importance of CEO styles for investment, financial, and organizational decisions in industrial firms. Focusing on specific attributes, Graham et al. (2013) showed that optimistic CEOs fund their balance sheet with more debt, in particular short-term debt, and that the risk tolerance of a CEO is positively related to acquisitions. Another attribute that has received ample attention in this literature is the impact of overconfidence on the part of CEOs on firm policies and performance. In a seminal paper, Roll (1986) showed how hubris among CEOs explains why bidding firms pay too much for their targets. Malmendier and Tate (2005) elucidated that overconfident CEOs overestimate the returns of their investment when there is enough internal capital available. They also showed that overconfident CEOs underinvest when they need to issue equity to fund investments, since they regard their company's stock as being undervalued. In addition, building on Roll, Malmendier and Tate (2008) showed that overconfident CEOs pay too much for target companies and engage in value-reducing mergers. The aforementioned studies all concerned industrial firms; meanwhile Ho, Huang, Lin, and Yen (2016) applied the overconfidence measure to the U.S. banking sector prior to the financial crisis. Banks with CEOs that exhibited overconfidence expanded their loan portfolios (especially in real estate loans) more aggressively than those with non-overconfident CEOs. This, in turn, led to greater loan losses and lagging operating and stock performance when the crisis unfolded.

Although these studies are just the tip of the iceberg, they illustrate the importance of CEO characteristics for firm policies, riskiness, and performance. Given this influence, instances of a change in CEO provide ample opportunity for further analyzing the impact of the person at the top. In this chapter we investigate the impact of CEO turnover at local banks that are members of a single cooperative organization in Europe. These banks enjoy a high degree of autonomy, which enables their CEOs to influence their financial performance. We investigate this impact of the CEO around the time of a CEO change. Our evidence shows that, in a new CEO's first year, the financial performance of the bank declines significantly. Since the banks we studied are not listed, financial performance is measured by return on assets (i.e., net earnings divided by assets), similar to Demirgüç-Kunt and Huizinga (2001) and Iannotta, Nocera, and Sironi (2007). The drop in return on assets equaled 0.08 percentage points, which was also economically large, representing 23% of the return on assets' standard deviation. When we included a lagged effect in the second year, the total decline over the first two years increased to 0.17 percentage points.

This decline seems not to have been caused by a difference in quality[1] between the exiting and incoming CEO, since the decline in performance is observed independent of the reason for a predecessor's departure. If the overall decline were attributable to quality differences between the CEOs, then the successors of CEOs who were being promoted (an act that testifies to their high quality) would be expected to show the largest decline in performance in the group. Yet, the opposite is true: the decline in performance is smallest for banks where a CEO has left as a result of a promotion. Nor does an alternative interpretation that new CEOs need time to adjust to their new bank explain the result, since we observed no material impact on operating performance (i.e., operating income minus operating costs).

By replacing the return on assets (dependent variable) with the change in loan loss provisions, we observe that the decline in the former in the first year after a change of CEO is caused almost entirely by an *increase* in the latter. This result can be interpreted in two ways: 1) the predecessor had been too lenient in taking provisions for non-performing loans and correction was needed or 2) the new CEO is taking an earnings bath. The results point to a combination of both effects, since provisions significantly *decrease* – in amounts similar to the *increase* in the successor's first year – during the

[1] Quality should be interpreted as the attributes that are relevant for leading a local bank, cf. Jenter, Matveyev, and Roth (2016).

second-to-last year of the predecessor and the third year of the successor. The decrease in provisions in the second case also makes it improbable that successors are more cautious than their predecessors, since it cannot be regarded as prudent to completely deplete the buffer in provisions two years after it has been built up.

Classifying loans as impaired is not without consequences. Since increases in impairments negatively affect a bank's capital position, such an action inhibits its room to provide credit to customers, especially in an environment with increasing capital requirements. In addition to this indirect effect on the economy, it also has a direct impact on clients and the bank itself. If a loan is classified as impaired, the bank puts the borrower under increased scrutiny, resulting in additional costs for the client and the bank. For instance, borrowers need to provide a plan to ensure minimal losses for the bank, while the bank needs to assess the plan's viability.

We used data for our analysis obtained from the cooperative bank under study, LinkedIn, and the national statistics bureau. The cooperative provided data on its balance sheet, income statement, number of members, and market share per bank for the period from 2010 to 2015. By enriching this data with information from the LinkedIn profiles of the CEOs, we were able to identify who was CEO at which bank at what time. Moreover, we have data on the reason for the CEOs' departures. Finally, to control for regional differences, we used data on local GDP from the national statistics bureau.

This chapter is related to three streams of the literature. The first is the literature on the impact of CEO turnover on firm value and performance. Jenter et al. (2016) focused on the impact of sudden CEO deaths on stock prices to assess whether incumbent CEOs are valuable to firms. The authors documented great heterogeneity in stock price reactions to sudden deaths. Overall, the stock price declines, which is consistent with the incumbent CEO being of value to the firm (Gabaix & Landier, 2008; Terviö, 2008). However, sudden deaths of older CEOs are associated with positive returns, which is not in line with the theoretical predictions of Gabaix and Landier (2008) and Terviö (2008) and indicates that firm value can increase after CEO departures. More relevant to our setting is that Jenter et al. found no impact of CEO death on operating performance or profits. This contradicts the finding of Bennedsen, Perez-Gonzalez, and Wolfenzon (2006), however, who documented a decline in operating profitability for private enterprises after a CEO dies.

When a CEO dies, the reason for departure is undisputed, and this provides a clean setting for measuring the impact of the newly appointed CEO on firm value and performance. Other reasons for CEO departure, especially dismissal, have also received much attention in the literature. The forced departure of CEOs has been used to study board effectiveness and board monitoring of the CEO. Three important factors related to this type of CEO departure are firm, industry, and market performance. Jenter and Lewellen (2010) showed that the probability of a dismissal is significantly higher after poor firm performance, while Jenter and Kanaan (2015) documented that downturns in industry and market performance increase the likelihood of dismissal. We contribute to this strain of the literature by relating the cause of CEO departure to bank performance in the final year of tenure.

A subfield of the CEO turnover literature is concerned with earnings management around a CEO change. This is the second stream of literature we relate to. An early example of this is Moore (1973), who documented larger income-reducing adjustments – a tactic at the discretion of the CEO – in firms experiencing management changes than in firms without personnel changes. Strong and Meyer (1987) and Pourciau (1993) corroborated this result, with the latter focusing exclusively on unanticipated changes in CEO, and found a reversal in performance in the second year after the change. Most of these studies do not single out a particular industry. An exception is Bornemann, Kick, Pfingsten, and Schertler (2015), who focused exclusively on German savings banks. The authors documented significant increases in discretionary expenses in the first year of a new CEO. This increase in overall discretionary expenses comprised two opposing forces: an increase in provisions for loan losses and a decrease in reserves for general bank risks. Furthermore, they found that new CEOs hired from outside the bank incurred larger discretionary expenses than those from inside the bank, which is consistent with the results of Strong and Meyer. Finally, the increase in discretionary expenses can be explained not only by a need to clean up a bank poorly managed by the predecessor, but also by the new CEO taking an earnings bath.

This chapter is related to Bornemann et al. (2015) but differs in several respects. First, Bornemann et al. concentrated exclusively on earnings manipulation on the part of the new CEO, whereas we focus on the overall performance of the bank in terms of return on assets. We found that changes in return on assets in the CEO's first year can almost entirely be attributed to changes in loan loss provisions. Second, we extend the analysis by also considering the performance of departing CEOs in the last years before leaving and the performance of new CEOs after their first year. Third, Bornemann et al. focus on savings banks that are owned by cities,[2] whereas we consider 106 banks that are privately-owned by their members and part of one cooperative organization.

The third stream of literature to which we contribute is research on bank performance. Since the banks we studied are non-listed, we relied on their profitability to assess performance. We discuss several papers that also use return on assets as a dependent variable. Kok, Móré, and Pancaro (2015) conducted a recent study on the performance of European banks that suggests that low GDP growth is the main factor hampering bank profitability. Demirgüç-Kunt and Huizinga (1999) focused on the influence of market structure on profitability and documented that a higher ratio of banking assets to GDP and lower market concentration curb profitability. Approaching bank earnings from a corporate governance perspective, Iannotta et al. (2007) concluded that

[2]As of June 1, 2016, there were 409 savings banks, of which six were not owned by a city or multiple cities; see `https://www.dsgv.de/en/facts/facts-and-figures.html` and `http://www.verband-freier-sparkassen.de/en/`.

ownership structure matters, since mutual and government-owned banks perform worse than their private counterparts. Typically, the samples in these studies are composed of different types of banks (i.e., commercial, cooperative, and savings banks) from multiple countries. They must control for many variables in order to measure the impact of the variable of interest on the performance of the bank. Since the banks in our sample are all part of the same cooperative organization within one country, we have a unique setting for identifying the drivers of bank performance, in general, and the impact of CEO turnover on performance, in particular.

The remainder of this chapter is structured as follows. In Section 4.2, we describe the structure of the cooperative bank. In Section 4.3, we provide a description of the variables. In Sections 4.4 and 4.5, we discuss the data and summary statistics, respectively. Finally, Section 4.6 presents the results, and Section 4.7 concludes.

4.2 The Structure of the Cooperative Bank

A stylized overview of the structure of the cooperative bank we studied is provided in Figure 4.1.

We will work from the bottom to the top in discussing the financial cooperative's structure. The blocks at the bottom of the figure represent the local banks. Each local bank has an independent banking license and a governance structure composed of a Local Board of Directors (LBD), a Local Supervisory Board (LSB), and a Local Member Council (LMC). Separation between the LBD and the LSB is in accordance with the two-tier corporate governance system common in many European countries. The LBD manages the bank; its members are appointed by the LSB with the approval of the central institution. For its part, the LSB advises the LBD and monitors and assesses its performance within the context of collectively agreed principles and strategies. It also acts as the employer of the members of the LBD and thereby has the authority to appoint, suspend, and dismiss individual members in consultation with the central

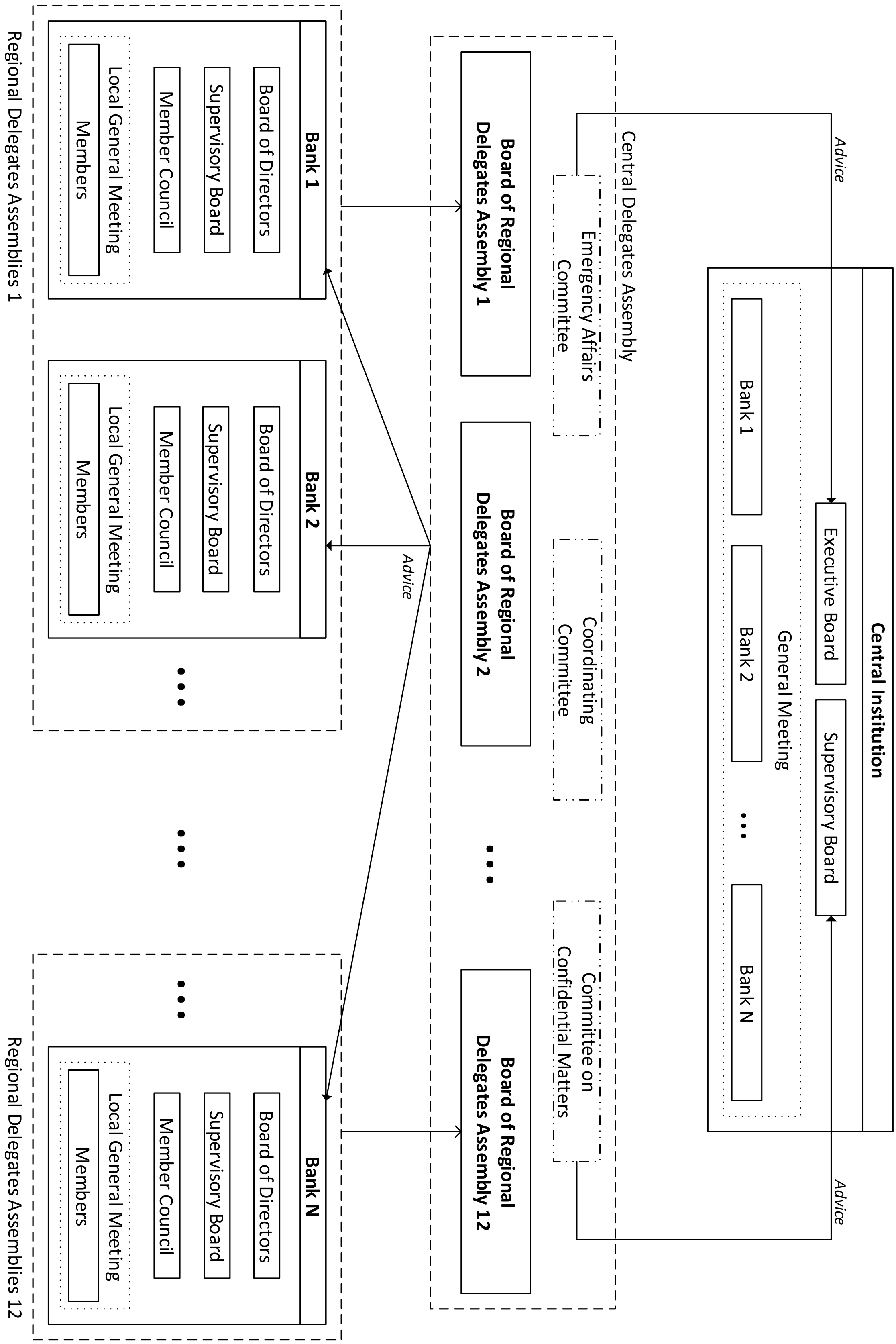

Figure 4.1. Governance structure of the financial cooperative.

institution. The LMC consists of 30 to 50 elected members from the local banks. It appoints, in consultation with the central institution, the members of the LSB, adopts the financial statements, and decides how money reserved for the local community is spent. Other members of the bank who are not part of the LMC can have a say in pivotal decisions through the Local General Meeting.

The central institution of the financial cooperative plays a more supervisory and accommodating role. In addition to its involvement in nominating, appointing, and dismissing members of the two local boards for each bank, it develops financial products, sets policies (e.g., on human resources and security), and provides access to the financial markets for local banks. Nonetheless, local banks operate largely independently of the central institution in their day-to-day business, deciding such matters as which clients to take on, company loan rates, bank strategy, marketing, and personnel (hiring and firing) for themselves. Conversely, the local banks can also exert influence on the workings of the central institution. This occurs through the auspices of the Central Delegates Assembly (CDA) (see the middle level in Figure 4.1). The local banks are organized into multiple Regional Delegates Assemblies, the boards of which make up the representatives of the greater CDA. The CDA is regarded as the "parliament" of the cooperative and endowed with two main tasks: 1) providing advice to the local banks, the Executive Board of the Central Institution, and the Local General Meeting for all of the banks and 2) adopting rules for the local banks and approving the budgets granted to them by the central institution.

Finally, the central institution (see the top level of Figure 4.1) is in its turn governed similarly to the local banks. It is composed of an Executive Board, a Supervisory Board, and a General Meeting. The Executive Board is comparable to the LBD on the local bank level, but now responsible for the entire group. The Supervisory Board has the task of monitoring the Executive Board. The General Meeting, in which all local banks are represented, resembles the LMC. It is responsible for adopting the consolidated financial statements, as well as discharging the Executive and Supervisory Boards.[3]

The position of local banks within the overall organization provides for an interesting balance between homogeneity and heterogeneity in our sample. Since all of the local banks are part of one organization, the sample is homogeneous, but the fact that they have relatively large autonomy – as reflected by each having their own banking license, for example – makes it heterogeneous. The homogeneity enables us to control for unobservable factors that are constant across banks but can change over time, such as internal rules and regulations, while the heterogeneity permits us to measure the impact of a local bank's CEO on bank performance.

4.3 Dependent and Independent Variables

In this section, we will first discuss the dependent variable and then the independent variables. Our analysis is composed of both a financial analysis and a CEO turnover analysis. In the financial analysis, we relate a bank's financial performance to bank-, industry-, and region-specific variables. The variables that turn out to be of importance for the bank's overall financial performance are then used as control variables in the CEO turnover analysis. We will therefore first introduce the variables used in the financial analysis and then discuss the CEO turnover variable at the end of the section.

Before we motivate our choice of variables, we want to comment on the use of stock and flow variables (I. Fisher, 1896). The value of a stock variable can be observed at one point in time, while the value of a flow variable is the result of an accumulation over a period of time. These two types of variables can also be combined in various ways through multiplication or division. Throughout the chapter, stock variables with subscript t are the values at the start of year t, which is equivalent to the values at the end of year $t-1$. Flow variables with subscript t cover the entire year t, that is, from

[3]For a discussion about how cooperative banks differ from commercial banks, see Ayadi, Llewellyn, Arbak, and de Groen (2010).

the end of year $t-1$ to the end of year t. As a consequence of using the values of stock variables from the start of a year (i.e., the end of the previous year), and since we have no data for 2009, we cannot include 2010 bank performance in the analysis. Therefore, we restricted our analysis to bank performance from 2011 to 2015, which resulted in 530 bank-year observations (i.e., five years for 106 banks).

4.3.1 Dependent Variable

Return on assets: The dependent variable represents the financial performance of a bank. We use net income, obtained during the year, divided by average assets.[4] We follow Barth, Nolle, Phumiwasana, and Yago (2003), Demirgüç-Kunt and Huizinga (1999), Demirgüç-Kunt and Huizinga (2001), Iannotta et al. (2007), and Kok et al. (2015) who used return divided by assets as a dependent variable. The first four papers used net profit before tax as the return, while the last paper used the net profit after tax. Since the banks in our sample are all operating in the same country, they share the same tax regime. We therefore follow the approach of Kok et al. and use the net profit after tax divided by assets.

Another item of note for this particular context: whenever a local bank is at risk of reporting a bottom line loss, it triggers an internal solidarity mechanism whereby funds flow from strong to weak performers to prevent this from happening. We therefore do not use the bottom line return to focus on individual local bank performance, but the return excluding this solidarity mechanism. To account for changes in asset size that occur during the year, the return is scaled by average assets. The average is taken over the assets at the start and end of the year.

4.3.2 Independent Variables

We will start by discussing the variables for measuring bank characteristics. These control variables were selected in line with previous studies such as Barth et al. (2003), Demirgüç-Kunt and Huizinga (1999), Demirgüç-Kunt and Huizinga (2001), Iannotta et

[4] Throughout the chapter, we will omit the word average.

al. (2007), and Kok et al. (2015). In the second part of the section, we focus on CEO turnover.

Bank Characteristics

Size: McAllister and McManus (1993) discuss two factors relating size to the costs of a bank. The first is economies of scale, which enables a bank to spread fixed costs over a larger earnings asset base. Their paper documented returns to scale for U.S. banks of sizes up to $500 million and no returns for larger banks. Altunbas and Molyneux (1996) similarly documented economies of scale for European banks. By contrast, Berger, Hanweck, and Humphrey (1987) found diseconomies of scale, but at the same time pointed to enhanced earnings potential associated with those costs, which renders the net impact on bank profitability unclear.

The second factor discussed in McAllister and McManus (1993) is the greater ability of larger banks to diversify, leading to lower funding costs. They argued that more-diversified banks need less equity, which is generally regarded as the most expensive source of funding. Although the asset diversification argument brings benefits in terms of reducing risk while achieving a similar level of income, the implication of lower funding costs does not apply in our case because a local cooperative bank does not have shareholders. Nevertheless, positive economies of scale and diversification of assets leads us to expect a positive relationship between size and financial performance.

Retail loans to assets: In characterizing the assets of a bank, a distinction is usually made between loans and securities (e.g., Iannotta et al., 2007). However, in our sample, the balance sheet of the median bank is composed almost entirely of loans (both retail and company), at 92%. The remaining 8% is composed of 5% excess funds, which are deposited at the central institution, and 3% other assets. Since there are no securities on the balance sheets of the local banks, we measure differences on the asset side by using retail loans to assets as an independent variable. Moreover, mortgages comprise 99.5% of the retail loans on the books; hence, to determine the expected sign of retail loans to assets on bank profitability, we restrict our attention to mortgages. The banks operate in a national mortgage market characterized by a low incidence of default. This large mortgage portfolio thus leads to a steady stream of income with low risks. Loans to companies, on the other hand, are more risky and, therefore, have higher interest rates. It is unclear a priori what the overall impact of these opposing forces will be on bank profitability.

Equity to assets: Berger (1995b) documented a strong positive link between the equity to assets ratio and profitability. The explanation for that relationship is twofold. First, more equity leads to a lower required return on equity due to the lower riskiness of the bank. This lowers the equity funding costs, which, ceteris paribus, increases profitability. Since the local banks in our sample do not have shareholders demanding a rate of return, this argument does not apply. Second, when we assume that not all earnings are paid out as dividends, larger profitability leads to higher retained earnings, which in its turn increases the equity to assets ratio. Since, in our case, the cooperative bank retains all of its earnings, this effect is highly relevant.

Berger (1995b) discussed two reasons for a negative association between equity and earnings. First, low equity funding implies more interest-bearing liabilities, which increases the tax shield. Second, less equity, ceteris paribus, brings a bank closer to default, which increases the value of the explicit guarantee provided by deposit insurance. The first argument applies in our case, while the second does not, since there is no heterogeneity among the local banks in terms of the probability of default given their system of mutual support, whereby they guarantee one another's survival. Since the retention-of-earnings argument predicts a positive and the tax shield argument a negative association between performance and equity to assets, we refrain from a hypothesis.

Deposits to assets: Besides equity, the second major form of funding for the local banks is retail and company deposits. More than two thirds of the deposit base is composed of retail deposits. On the one hand, Iannotta et al. (2007) argue that deposits are a cheap source of funding that can increase net interest income; on the other, retail deposits can require an extensive branch network, which increases operating costs (Demirgüç-Kunt & Huizinga, 1999). The cheap funding argument applies to our case, since the main alternative source of funding – that is, funds from the central institution (see below) – carries a higher interest rate.[5] However, despite the fact that depositors increasingly bank online and many bank branches are closing, we still expect to find a positive relationship between deposits and branch network costs. Consequently, we refrain from a prediction on the relationship between deposits to assets and return on assets.

Debt to central institution to assets: The final source of funding, comprising 16% for the median bank in our sample, comes from the central institution. As stressed above, funding from the central institution is more expensive than deposit funding. Hence, greater reliance on the central institution lowers net interest income. Furthermore, a greater dependency on the central institution might be a reflection of poor management, indicating an inability to attract sufficient deposits or earn and retain sufficient earnings. On the other hand, when the loan book of a local bank grows rapidly and the deposits or retained earnings needed to fund this growth cannot keep up, the gap can be filled by funding from the central institution. This could then result in a positive correlation between central funding and return on assets. We are not sure which of these opposing predictions will be of greater importance in our sample and therefore do not know what the relationship will be between central institution debt and financial performance.

Impaired loans to total loans: When a bank expects that the notional value of a loan and/or its accrued interest will not be fully repaid, it takes a provision and the loan is labelled as an impaired loan.[6] The value of impaired to total loans

[5]The other source of funding, equity, is more difficult to adjust (on short notice), since it can only be increased by retained earnings.

[6]Note that we are measuring the impaired loans accumulated in current *and* previous years. This should be distinguished from provisions taken in the current year, which lower the earnings of the bank

thus serves as a proxy for the quality of a bank's loans, and the value of the impaired loans can be seen as an indication of the riskiness of the overall loan portfolio (Iannotta et al., 2007). To compensate for their higher probability of default, these loans are also likely to yield higher interest income. Moreover, a low number of impaired loans overall can be a reflection of how much resources are spent screening and monitoring these loans, which involves high operating costs and consequently low performance (Berger & DeYoung, 1997). As a result, both arguments predict a positive relationship between the number of impaired loans and financial performance. On the other hand, when loans are classified as impaired, the bank will probably have to expend more effort recouping them. This negative relation between impaired loans and efficiency, which is possibly mediated by poor management, leads to a negative association between impaired loans and performance (Berger & DeYoung, 1997). In sum, these opposing predictions make the expected relationship between impaired to total loans and bank performance uncertain.

Member ratio: The cooperative structure of the bank allows its customers to become members and exert their influence through the member council. Although membership is not mandatory, on average more than 23% of the customers are members of the cooperative bank. We expect the member ratio to be positively related to the bank's overall financial performance since we interpret it as a proxy for the loyalty of the bank's customers. Increased loyalty will induce customers to obtain their banking products to a greater extent from their local bank, which enhances the earnings potential of that bank and should lower switching behavior, implying a stable and low-cost funding base.

Market share: Two theories, discussed in Berger (1995a), predict a positive relationship between market power and performance. The relative-market-power hypothesis states that banks with a large market share are able to extract monopolistic rents that translate into high rates on loans and low interest on deposits. An

in that year.

alternative theory states that a large market share is the reflection of excellent bank management and/or superior production technology, which also translates into high profitability (see Molyneux & Forbes, 1995). On the other hand, market power could also induce management to opt for the "quiet life" and scale back on risk-taking (Edwards & Heggestad, 1973). This implies that excessive profits are forgone for a lower, but more certain, stream of income and predicts a negative correlation between market power and profitability. As a result of these conflicting hypotheses, we refrain from a prediction on the relationship between market share and financial performance.

Local GDP per inhabitant: Similar to Barth et al. (2003) and Demirgüç-Kunt and Huizinga (1999), we account for cross-region economic vitality differences by including the local GDP per inhabitant for a bank's working area. The location of a bank determines its earnings potential to a large extent. For example, in an urban area, the potential number and amount of lucrative company loans is larger than in a rural area. On the other hand, the financial cooperative we studied has a large market share in the food and agriculture sector, which might lead to better earnings prospects in rural areas. Therefore, the net effect of GDP per inhabitant on performance is uncertain.

To measure local GDP, we relied on the working areas of the local banks, which are non-overlapping and cover the entire country. Local banks generally respect these boundaries and do not service clients from other working areas. The exceptions to this rule are when someone moves to another part of the country and keeps a deposit account at their previous bank or when a holding company with retail stores throughout the country takes out a loan in a region where one of the stores is located instead of the region in which it resides. Since the national statistics bureau does not report a local gross domestic product at the neighborhood level – that is, the level at which the cooperative has defined the working areas for its banks – we devised our own proxy for the economic strength of the community serviced by a bank. A stylized example is presented in Figure 4.2.

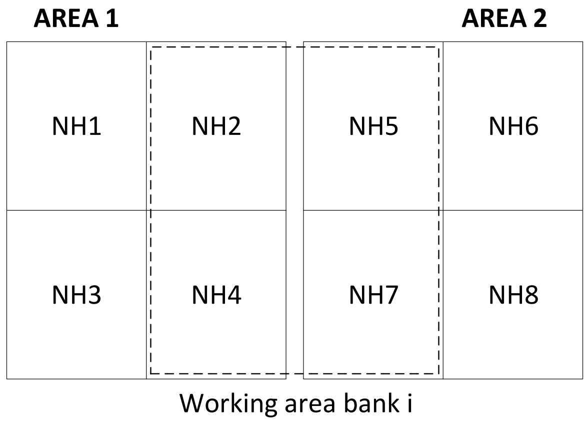

Figure 4.2. Stylized example of the approximation of the local GDP for the working area of bank i.

Assuming there are two areas, $A1$ and $A2$, and each of them is divided into four neighborhoods, $NH1$ to $NH4$ and $NH5$ to $NH8$, respectively, the working area of bank i contains neighborhoods two and four of $A1$ and five and seven of $A2$. From the national statistics bureau, we have GDP information on the area level, that is, $A1$ and $A2$, and the number of inhabitants at the neighborhood level, that is, $NH1$ to $NH8$. To derive a proxy for the economic strength of the working area, we summed up the weighted GDPs of $A1$ and $A2$, where the weighting factor is the share of inhabitants of an area that fall into the working area. In this particular case the local GDP of the working area of bank i would be equal to:

$$\begin{aligned} localGDP_i = & GDP_{A1} \cdot \frac{NH2 + NH4}{NH1 + NH2 + NH3 + NH4} + \\ & GDP_{A2} \cdot \frac{NH5 + NH7}{NH5 + NH6 + NH7 + NH8}, \end{aligned} \tag{4.1}$$

where GDP_{A1} is equal to the gross domestic product of $A1$ and $NH2$ is the number of people who live in neighborhood two.

The generalization of Equation (4.1) for bank i at time t then becomes:

$$localGDP_i^t = \sum_{j=1}^{N} \left(GDP_j^t \cdot \frac{NH_i \wedge NH_j}{NH_j} \right),$$

where N is the number of different areas ($A1$ and $A2$ in the stylized example) in the working area of bank i. GDP_j^t is the GDP of area j at time t. NH_j is the number of inhabitants in area j, and NH_i is the number of inhabitants in the working area of bank i. Hence, $NH_i \wedge NH_j$ is the number of inhabitants living in the neighborhoods of area j who are also situated in the working area of bank i. Since the assignment of neighborhoods to areas changes throughout the years, we base the weights on population data from 2014. To obtain the number of inhabitants in the working area of a bank, we used the number of inhabitants on the area level and applied the same methodology as for computing the local GDP to determine which fraction of the inhabitants in an area should be ascribed to a bank. Finally, we divided both numbers to arrive at the local GDP per inhabitant.

CEO Turnover

CEO turnover: To measure the impact of a newly appointed CEO on the bank's financial performance, we add a dummy variable that equals 1 in the first year of the new CEO. In an alternative specification, we also allow for a lagged effect by adding a dummy variable equal to 1 in the second year of the new CEO, as well. In predicting the impact of a change of CEO on bank performance, we focus on the four main components of net earnings (i.e., the numerator of return on assets): net interest income, commissions, operating expenses, and provisions for credit risks. Insofar as a difference in ability between a predecessor and a successor arises, it might influence the first three elements. In other words, when a high-performing CEO is replaced by an average or low performer and the successor is able to influence performance, we expect a negative impact in terms of a decrease in net interest income and commissions and/or an increase in costs. The opposite would occur when a low performer is replaced by an average or high performer. In addition to this first line of reasoning, another theory is that new CEOs might need time to get used to their new situation, which could hamper performance in the initial year(s) after a change. When the quality of the predecessor is not systematically different from the quality of the successor, the first situation would, on average, have no effect on performance, while the second would have a negative impact.

It is also important to note that the final component of net earnings, provisions for credit risks, should be distinguished from the other criteria because it is largely unrelated to the CEO's managerial competence. Following Bornemann et al. (2015), we differentiate between two reasons for taking provisions. First, the action might be the result of a difference in opinion between the old and new CEOs regarding the overall riskiness of loans. Second, the new CEO might be using the first year to take an earnings bath and blame the old CEO for the resulting bad performance. This opportunistic behavior is labeled taking a "big bath" (see Moore, 1973; Pourciau, 1993). In the first situation, the impact on provisions and thus performance is unclear, while the second avenue would increase provisions and lower performance. Although it is unsure which of these channels will dominate, taken together, they predict a negative impact on results. We therefore expect a decline in financial performance after a change in CEO.

4.4 Data

We relied on three main sources of data for this chapter: the financial cooperative under study, the national statistics bureau, and LinkedIn. In this section, we discuss the data and provide summary statistics.

4.4.1 Bank Data

The financial cooperative provided annual data on its balance sheet, income statement, number of members, working areas, and market shares in two different sectors (residential mortgages and food and agriculture) per bank for the 2010–2015 period.[7,8] In addition, we were provided with the names of the CEOs of the local banks during that sample period. In contrast to the financial data, this latter dataset was incomplete and required additional work (see Section 4.4.3).

During the period we considered, 41 banks merged. Typically, one bank was the *leading* bank and the other the *liquidated* bank. Figure 4.3 provides an example.

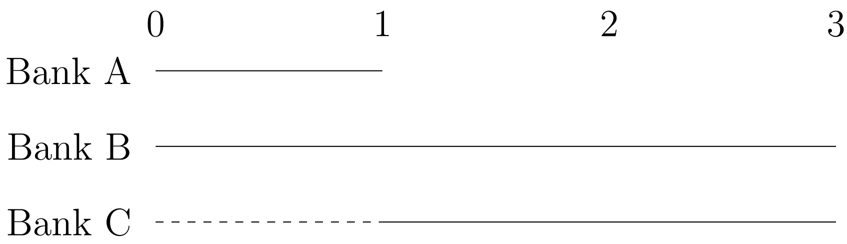

Figure 4.3. Banks A and B merge at Time 1. Bank B is the leading bank and Bank A is the liquidated bank. Bank C is equal to the merged entity as of Time 1. Before the merger (from period 0 to 1), Bank C is equal to the combination of the individual Banks A and B.

Suppose a merger takes place at Time 1 between the liquidated Bank A and the leading Bank B. That means that after time period 1, Bank A no longer exists and is incorporated into Bank B. To ensure comparability before and after the merger, we define a hypothetical Bank C, which is the equivalent of Bank B from Period 1 to Period 3. In the pre-merger period, i.e., from Periods 0 to 1, we artificially "merge" Bank A with Bank B to form Bank C. Hence, for this period, we combine the financial data of Banks A and B. In the sample, we then only include Bank C and do not consider Banks A and B.

For the assignment of a CEO to a bank, we apply the rule that the CEO of the leading bank becomes the CEO of the "combined" bank. Hence, in the above example,

[7]Note that the market share data provided for the two sectors is not measured the same way. The market share in mortgages is based on bank data and data from the cadastre. The market share is computed as the euro amount of mortgages on the bank's balance sheet divided by the total euro amount of mortgages in the working area of the bank. The market share for the food and agriculture sector is based on an annual survey of the companies in the working area of the bank. It is defined as the number of surveyed companies in that sector that perceive the bank as their house bank divided by the total number of surveyed companies in the food and agriculture sector.

[8]This data is not publicly available and was provided by the bank.

the CEO who led Bank B from Periods 0 to 3 becomes the CEO of Bank C in Periods 0 to 3. This resulted in 106 banks for the period from 2010 to 2015. We also requested financial data for the period before 2010, but this data was either not consistent with the data after 2010 or unavailable.

4.4.2 National Statistics Bureau Data

As a proxy for the economic activity of a local bank's working area, we gathered data from the national statistics bureau on GDP levels and number of inhabitants. In 1970, the country under study was divided into 40 areas by applying a nodal classification system which was based on commuter flows. That is, each area has a central node (a city) and a surrounding area depending on it. On this level, we have data for GDP levels and the number of inhabitants from 2010 to 2015. Independent of this structure, the country is divided into multiple provinces, each consisting of several municipalities. Each municipality is in turn further divided into quarters and neighborhoods. On the neighborhood level, we obtained data for the number of inhabitants in 2014.

4.4.3 CEO Data

The previous two data sources cover bank-, industry-, and region-specific variables. Yet, in order to assess the impact of the CEOs on bank performance, we also need information on their exit and start dates. The financial cooperative provided us with this information, which we enriched with information from the CEOs' LinkedIn profiles. If the information between these two sources did not correspond, we relied on the dates provided by the CEOs on their LinkedIn profiles, because we considered that to be more trustworthy. This combined dataset was then used to assign the CEOs to bank-years according to the following assignment rules:

1. The CEO in charge for the majority of the year, with a minimum of six months, is assigned as CEO. Hence, if the predecessor left on 31-5-2011 and the successor started on 1-6-2011, the latter was assigned to the bank for 2011;[9]

[9]This assignment rule might introduce a bias when there are CEOs who were at the helm for less

2. If both the predecessor and the successor were CEO for six months each – that is, the predecessor left on 30-6-2011 and the successor started on 1-7-2011 – we assigned the bank to the successor;

3. If a CEO started at a bank as an ad interim CEO and subsequently became the permanent successor, the bank was assigned to the new CEO as of the start of the ad interim period;[10]

4. Bank-years not assigned to a particular CEO after applying the above rules were assigned to the predecessor.

As indicated by Rule 4, a few bank-years remained after applying Rules 1 through 3 above for which no CEO had been assigned. For instance, if the predecessor left on 1-8-2011 and the successor started on 1-8-2013, the bank was assigned to the successor for 2014 and to the predecessor through 2011, but it lacked an assignation for the intervening years, 2012 and 2013. Since our main analyses focus on the impact of the successors, it is important that their moment of arrival not be modified. Of less importance is when the predecessor left. These empty years were therefore assigned to the predecessor. In sum, this procedure ensures that a bank-year is only assigned to the successor once they have been CEO for at least six months. We will subsequently refer to this data file as the successor file.

In addition to analyses focusing on the impact of the successor, we are interested in the relationship between the departure of a CEO and bank performance. For instance, we wonder whether CEOs who are being promoted were strong performers in their final year before departure. In that case, our focus shifts from the successor to the predecessor and, as a result, assignment rules number 2 and 4 change. When both predecessor and

than six months. These CEOs would then not be assigned to a bank-year because of the six months rule. Fortunately, this did not occur in our dataset.

[10]If these cases frequently occurred in our dataset and would drive the overall result, the following interpretation might apply: an ad interim CEO takes an earnings bath to blame the previous board, which decreases the likelihood of other board members to become the new CEO and at the same time increases the ad interim CEO's chances to become the permanent CEO. Only in four of the 80 CEO changes an ad interim CEO became the permanent CEO. Hence, these cases are unlikely to drive our overall results.

successor are CEO for six months each, the bank-year is assigned to the predecessor. Furthermore, the empty years are now assigned to the successor, because the more important criterion is when the predecessor left, rather than when the successor started. Consequently, these rules ensure that a bank-year is only assigned to the predecessor when they have been CEO for at least six months. We will subsequently refer to this data file as the predecessor file.

4.5 Summary Statistics

In this section, we first present summary statistics for the bank characteristics; then we present those for the CEO turnover variables.

4.5.1 Bank Characteristics

Table 4.1 contains summary statistics for the characteristics of the banks.

Table 4.1. Summary statistics of bank characteristics. The statistics are computed over time and across banks. Assets are measured in thousands of euros and Local GDP per inhabitant in euros. The other variables are expressed as percentages.

	Mean	SD	Min	Max
RoA (%)	0.37	0.34	-1.28	1.54
Assets ('000 €)	2,720,498	1,344,617	235,322	10,935,552
Retail Loans to Assets (%)	59.27	8.15	31.19	79.67
Mortgages to Retail Loans (%)	99.41	0.33	93.61	99.76
Equity to Assets (%)	8.61	2.53	0.37	16.61
Deposits to Assets (%)	71.92	9.67	35.10	90.26
Debt to Central Institution to Assets (%)	17.35	10.70	0.00	62.38
Impaired Loans to Total Loans (%)	1.42	0.65	0.14	4.30
Member Ratio (%)	26.01	7.49	9.12	57.39
Market Share in Mortgages (%)	24.59	7.97	8.69	51.84
Market Share in Food/Agri (%)	82.77	7.18	55.56	96.08
Local GDP per Inhabitant (€)	36,157	8,953	17,549	71,121
Number of observations	530			

The statistics were computed over time and across banks. The average return on assets of a local bank equals 0.37%, with a minimum of -1.28% and a maximum of

1.54%. The average size of a bank, measured by assets, equals €2.7 billion. The third row shows that retail loans, which are almost entirely composed of mortgages (fourth row), account for 59% of total assets. On the liability side, equity accounts for 8.6% of the balance sheet. The minimum and maximum values of 0.37% and 16.61% show, respectively, that some member banks are almost depleted of capital, while others have plenty. Deposits (retail and company) account for 72% of the funding and debt to the central institution for 17%. Considering the minimum and maximum values of this latter variable, some banks need no funding from the central institution at all, while others require up to 62%. The percentage of impaired to total loans ranges from 0.14% to 4.30%, with an average of 1.42%. The market share of 83% on average in food and agriculture is remarkable. Finally, local GDP per inhabitant highlights the variation in economic activity between the working areas.

4.5.2 CEO Turnover Variables

Since our main analyses focus on the impact of a successor on bank performance, we discuss here the characteristics of that data file.[11] Seventy of the 106 banks experienced a CEO changeover once between 2010 and 2015, and for five banks, the CEO changed twice. We classify the causes for these 80 departures into three categories: positive, neutral, and negative. The first category consists of cases where a CEO was promoted and the third of cases where they were dismissed or demoted. In the neutral category, the departure of the CEO was unrelated to performance or involved switching to another bank of similar size. An overview of the number of departures and the associated reason is provided in Table 4.2.

[11] See Section 4.4.3 for a discussion of the differences between the data files focusing on predecessors and successors.

Table 4.2. Classification of manager departures into three categories. A positive departure is associated with an improvement in job position, while a negative departure implies a deterioration in position. The neutral cases fall neither into the positive nor the negative category. Each main category is then further classified into subcategories.

	#
Number of changes	**80**
Positive	**25**
Promotion between local banks	21
Promotion to central organization	4
Neutral	**32**
Retirement	17
Neutral between local banks	12
Voluntary leave	2
Death	1
Negative	**23**
Forced leave	18
Supernumery	3
Demotion	2

The positive, neutral, and negative categories are quite evenly distributed. Each of these categories is then divided into subcategories as indicated in the table. Four people were promoted within the cooperative from their CEO position at a local bank to a more prestigious position at the central institution. Seventeen CEOs left because of retirement; two left voluntarily; and one died unexpectedly while in charge of the bank. Eighteen people were forced to leave, while three were dismissed because they were superfluous after a merger of two banks. The two remaining subcategories, labeled promotion and neutral between local banks, involved departures that were trickier to classify. In each of these 33 cases, the CEO left one local bank for another local bank. We chose to classify a departure as a promotion when the new bank was at least 10% larger in assets than the old bank. The other cases were classified as neutral.[12,13]

[12] Alternatively, we could have classified a transition from a larger to a smaller bank as a demotion. However, the central institution assured us that the bank would not let an underperforming CEO at one bank switch to a smaller bank.

[13] In cases where a CEO leaves one local bank for another and one of these banks merged thereafter, our practice of combining the balance sheets of the merged banks in the years leading up to the merger could produce an erroneous classification for the departure. We therefore conducted an internet search for these cases to manually check the size of the pre-merger leading bank. In principle, we used the asset

4.6 Results

In this section, we present our results. In Section 4.6.1, we relate financial bank performance to bank characteristics. In Sections 4.6.2 to 4.6.4, we assess the impact of CEO turnover on bank performance.

4.6.1 Bank Characteristics

We estimate the following fixed effects model:

$$RoA_{it} = \alpha + \kappa_t + \sigma_i + \beta X_{it} + \varepsilon_{it}, \tag{4.2}$$

where RoA_{it} is the return on assets for bank i at time $t \in \{2011, 2012, 2013, 2014, 2015\}$ Time and bank fixed effects are indicated by κ_t and σ_i, respectively, and α is the constant. X_{it} represents the control variables for bank i at time t. We estimate the model with the fixed effects specification because we do not expect the strict exogeneity assumption to be violated (Cameron & Trivedi, 2009, pg. 271).[14,15] In the fixed effects model, we include bank characteristics that are assumed not to change over time, such as the bank's culture, and time effects that do not differ between banks, such as, a nationwide economic downturn. Moreover, to correct for arbitrary heteroskedasticity and arbitrary correlation over time within the local bank (i.e., within-group correlation), the error terms are clustered at the bank level. Finally, to limit the impact of outliers on the results, we apply a logarithmic transformation to the size (assets) and local GDP per inhabitant variables.

size in the year prior to the merger. If this was not available, we used the last year before the merger for which there was data available. When we were not able to identify the size of the pre-merger leading bank, we estimated it by applying the same division in assets between the leading and liquidated bank as we observed in the cases where we were able to identify the size of the pre-merger leading bank.

[14] We also estimated a first-difference specification of the model. This changed the results in two ways: the size of the bank became significantly negatively related to performance at the 5% level instead of at the 10% level. Moreover, local GDP per inhabitant was now significantly positively related to performance at the 5% level.

[15] We tested for the appropriateness of the random effects model by using a robust version (i.e., cluster-robust standard errors) of the Hausman test (Cameron & Trivedi, 2009, pp. 266–268). The null of equality of coefficients between the fixed and random effects model was rejected (p-value of 0.0000). Hence, the random effects model is not appropriate in this setting.

Table 4.3. Results of a fixed effects model with return on assets as dependent variable. Balance sheet characteristics, local GDP per inhabitant, market shares, and member ratio are the independent variables. Time and bank fixed effects are included, and the error terms are clustered per bank. The p-values are reported in parentheses under the parameter estimates.

	(1)	(2)
Log(Assets)	-0.829*	-0.825*
	(0.083)	(0.085)
Retail loans to assets	0.0122	0.0123
	(0.153)	(0.148)
Equity to assets	-0.157***	-0.150***
	(0.000)	(0.001)
Impaired loans to total loans	0.0214	0.0281
	(0.708)	(0.622)
Debt to central institution to assets	-0.00760	
	(0.316)	
Log (Local GDP per inhabitant)	0.804	0.809
	(0.227)	(0.226)
Market share in mortgages	0.00568	0.00565
	(0.200)	(0.202)
Market share in food/agri	0.00208	0.00208
	(0.743)	(0.744)
Member ratio	-0.00620	-0.00621
	(0.396)	(0.397)
Deposits to assets		0.00759
		(0.312)
Observations	530	530
Bank fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Clustering level	Bank	Bank

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We estimated two specifications of the fixed effects model presented in Equation (4.2). In the first specification, we included debt to the central institution to assets as an independent variable, while this variable is replaced by deposits to assets in the second specification. We could not include both variables in one specification because it would have led to multicollinearity, since the sum of these two variables and equity to assets is approximately equal to 1.

The results are similar for Specifications 1 and 2. Size, as measured by log(assets), and equity to assets are negatively related to return on assets at the 10% and 1% levels, respectively. Positive economies of scale (Altunbas & Molyneux, 1996; McAllister & McManus, 1993) and the ability to diversify (McAllister & McManus, 1993), which predict a positive association between size and performance, do not apply in our case. On the contrary, our results suggest diseconomies of scale, which might be attributable to the increased complexity of a larger bank. In addition, large banks are primarily located in large cities, where competition is fiercer[16] than in rural areas and the impact of the economic recession(s) might have been more severe.

Berger (1995b) points to a lower tax shield for banks with a great deal of equity as an explanation for the negative association between equity to assets and profitability. Alternatively, rapid expansion on the part of a bank in preceding years would lengthen its balance sheet and could lead to a decrease in the equity to assets ratio in cases where retained earnings are insufficient for keeping up with the expansion. In an unreported regression, we tested this hypothesis by adding asset growth in the previous year as an independent variable. In that specification, the association between equity to assets and profitability remained unchanged.

Although insignificant, the existence of a larger fraction of retail loans (which in our case consist almost exclusively of mortgages) is positively related to performance. The low default rate and steady income associated with mortgages seems to predominate over the higher interest rates associated with company loans. This is in line with the finding of Delis and Kouretas (2011), who documented that the low-interest-rate environment of the 2000s led to an increase in risk-taking at banks. Insofar as this resulted in an increase in company loans vis-à-vis mortgages, the banks that increased their riskiness

[16] Although we already proxy for competition with the market share variables for mortgages and food/agriculture, we do not have similar data for the most profitable market for local banks: company loans. Therefore, competition on this dimension (i.e., larger banks face more competition) could be partly captured by the size of the bank.

the most are the most likely to have experienced the deterioration of these company loans in the economic crisis, which unfolded during the years of our sample. Ultimately, this then also harmed their profitability.

The positive relationship between performance and local GDP per inhabitant is in line with the results of Barth et al. (2003) and Demirgüç-Kunt and Huizinga (1999). Moreover, when we estimate a first-difference specification of the model, that relationship becomes statistically significant at the 5% level. Finally, the member ratio, which we use as a proxy for customer loyalty, has an insignificant negative sign, while we expected it to have a positive impact on bank performance. A discussion contrasting the possible interpretations of this finding – that is, whether loyalty is not a determining factor in bank profitability or the member ratio is not a proper proxy for loyalty – is outside the scope of this chapter.

4.6.2 Impact of CEO Turnover on Performance

In this section, we use the statistically significant financial characteristics of the previous section and add dummies to measure the impact of CEO turnover on a bank's financial performance. We used the successor data file (see Section 4.4.3) for these analyses. We estimate the following fixed effects model:

$$RoA_{it} = \alpha + \kappa_t + \sigma_i + \beta X_{it} + \lambda_\tau E_\tau + \varepsilon_{it}, \tag{4.3}$$

where we have added the dummy E_τ with $\tau \in \{-1, 0, 1, 2, 3, 4, 5\}$, to Equation (4.2). Depending on the regression specification, we include a subset of these dummies. The dummy E_1 is equal to 1 in the first year of the new CEO and E_2 is equal to 1 in the second year of the new CEO. The last year of the previous CEO is indicated by E_0. To enhance readability, we omit subindices i and t for the dummy variables. To clarify how the dummies should be interpreted, we present a stylized example for a CEO changeover at Bank A in Table 4.4.

Table 4.4. Definition of dummy variables when CEO Mr. X is replaced by CEO Ms. Y at Bank A in 2012. Indicator variables E_τ with $\tau \in \{-1, 0, 1, 2, 3, 4, 5\}$, indicate two years before and five years after the change.

Bank	Year	Manager	E_{-1}	E_0	E_1	E_2	E_3	E_4	E_5
A	2011	Mr. X	0	1	0	0	0	0	0
A	2012	Ms. Y	0	0	1	0	0	0	0
A	2013	Ms. Y	0	0	0	1	0	0	0
A	2014	Ms. Y	0	0	0	0	1	0	0
A	2015	Ms. Y	0	0	0	0	0	1	0

In 2012, a change occurs whereby CEO Mr. X is replaced by CEO Ms. Y. In the year before the switch, E_0 is set equal to 1. In the first year after the change, that is, the first year of the new CEO, E_1 is set equal to 1. If the decision to change the CEO is exogenous, E_1 should be interpreted as the immediate impact on the return on assets of the new CEO. Subsequently, E_2 equals 1 in the second year of the new CEO and can be interpreted as the lagged impact of the CEO on return on assets. The other dummies should be interpreted analogously.[17]

In Table 4.5, we present the results when we include dummies in the baseline model. We restrict the set of control variables to the ones that were significantly related to return on assets in the analysis performed in Section 4.6.1. In the first specification, we estimate the model with only the control variables. In the second specification, we add the dummy to measure the impact of the new CEO on financial performance in the first year after the change. Finally, in the third specification, we also add a dummy for the second year of the new CEO to allow for a lagged impact.

[17] If a new CEO arrives in 2011, i.e., the first year for which we analyze bank performance, E_1 is set equal to 1 in 2011.

Table 4.5. Results for a fixed effects model with return on assets as dependent variable. We only include control variables that were significantly related to return on assets in Section 4.6.1. We include dummies for the first year of the new CEO, E_1, in Specification (2) and for the first and second years, E_1 and E_2, in Specification (3). Time and bank fixed effects are included, and the error terms are clustered per bank. The p-values are reported in parentheses under the parameter estimates.

	(1)	(2)	(3)
Log(Assets)	-1.109**	-1.140**	-1.156***
	(0.012)	(0.010)	(0.009)
Equity to assets	-0.155***	-0.156***	-0.154***
	(0.000)	(0.000)	(0.000)
E_1		-0.0765*	-0.0950**
		(0.058)	(0.019)
E_2			-0.0768**
			(0.048)
Observations	530	530	530

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results for the control variables are the same in all three specifications. Compared to the results of Section 4.6.1, the significance of size increases from the 10% to the 1% level. The second specification shows that in the first year of a new CEO, the return on assets drops significantly, with a p-value of the 5.8%. In economic terms, the impact is quite significant, since a change in CEO reduces the return on average assets by -0.08 percentage points in the first year, which equals 23% of the standard deviation of return on assets (see Table 4.1). When we also allow for a lagged effect in the change of CEO, Specification 3, we observe a significant decline in performance in both the first and second years after the change. Adding both effects amounts to a decrease in return on assets of 0.17 percentage points over the first two years.[18]

[18] Rajan (1994) documented that banks are more likely to increase their provisions when other banks in the same region increase their provisions. In order to check whether this phenomenon of "taking an earnings bath together" might also apply to our case, we rerun Specification 2 and 3 of Table 4.5 while clustering the standard errors on the regional instead of on the bank level. The regions have between 6 and 12 local banks. Naturally, the regression coefficients are the same. Moreover, the significance of the variables are also largely similar: including only the first year dummy (see Specification 2) increases the significance from the 10% to the 5% level, and including the first two years (see Specification 3) slightly

Before going on to analyze the various factors that could explain the decrease in performance (see Sections 4.6.3 and 4.6.4), we would like to first discuss a possible endogeneity issue. If we consider that bank performance might influence decisions about replacing a CEO, our setup could be considered vulnerable to the issue of reverse causality. For example, the CEO of a bank that is performing well, whether or not due to that CEO's influence, might be rewarded in the form of a promotion. In that case, strong prior bank performance has induced the CEO change. The exact opposite can happen when a CEO at a poorly performing bank is dismissed or demoted within the organization. As a stylized example, consider the case of strong performance on the part of bank i in year t, which leads to a high $\varepsilon_{i,t}$. If we assume that this implies that the CEO will be rewarded and therefore leave the bank in year t, this yields a positive correlation between $\varepsilon_{i,t}$ and $E_{1,i,t}$, that is, the first year of the new CEO. This would violate the exogeneity assumption and that renders a causal interpretation of the results problematic.

However, the method we used for assigning a CEO to a bank partially mitigates this problem, since the CEO who is at the helm for the longest portion of the year is classified as the CEO for that year. The problem described above therefore only occurs when a CEO is promoted in the first half of the year *and* the new CEO has no influence on the bank's performance until the end of the calendar year. In that case, the bank's performance in year t is determined by the leaving CEO and is correlated with the dummy variable equal to 1 in year t, that is, the first year of the new CEO. While such a case is rather unlikely, it could occur in our sample. We therefore resorted to an instrumental variable fixed effects (IV-FE) analysis.[19]

We look for exogenous variation that is correlated with the dummy variable $E_{1,i,t}$,

increases the significance of the first year and decreases the significance of the second year from the 5% to the 10% level. In sum, the results are robust to this alternative specification.

[19] Another motivation to perform an IV-FE analysis is the "romance of leadership" theory presented in Meindl, Ehrlich, and Dukerich (1985). The authors are worried about assigning too much power to leaders of organizations in influencing its outcomes. This concern of omitted variables, which can potentially account for the relationship we find, is mitigated with the IV-FE analysis.

the variable equal to 1 in the first year after the change of CEO but unrelated to bank performance in year t, except through the impact on the dummy variable. We rely on cases where CEOs left because they died unexpectedly or retired voluntarily. An unexpected death is most likely unrelated to the bank's performance in year t. Similarly, for CEOs who retire voluntarily (as opposed to a forced retirement, which should be interpreted as a disguised dismissal), it is likely that their departure is unrelated to bank performance. Hence, we define the following dummy variable for bank i at time t:

$$Vol\_Ret/Death_{i,t} = \begin{cases} 1 & \text{if a CEO retires voluntarily or dies unexpectedly in year } \boldsymbol{t-1}; \\ 0 & \text{otherwise.} \end{cases}$$

By setting the dummy equal to 1 *one year after* a CEO has left as a result of voluntary retirement or unexpected death, the variable is positively correlated with E_1, which equals 1 in the year after a CEO leaves (i.e., independent of the reason for leaving).

Before using this instrument, we assess the weakness of the instrumental variable (Cameron & Trivedi, 2009, pg. 194), since this could cause a decrease in the precision of estimates and, in addition, considerable finite-sample bias. An instrument is weak when the instrumental variable is not strongly related to the endogenous variable. As a diagnostic for weak instruments, we first check the correlation between the endogenous variable ($E_{1,i,t}$) and the instrument ($Vol\_Ret/Death_{i,t}$). A correlation of 0.44 with a p-value of 0.000 is the first sign that the instrument is not weak. Furthermore, the parameter for the instrument in the first stage (unreported) is positive and highly statistically significant (p-value of 0.000). In addition to these diagnostics, the formal test for weak instruments when errors are clustered, the Kleibergen-Paap rk LM statistic (Kleibergen & Paap, 2006; Kleibergen & Schaffer, 2007), yields a strong rejection of the null of having weak instruments (LM statistic of 18 and p-value of 0.0000). Hence, our analysis seems not to suffer from the weak instrument problem.

The IV-FE analysis was prompted by concerns about the exogeneity of the independent variable of interest. If this variable were exogenous, the IV-FE technique would be much less efficient than regular fixed effects estimation (Cameron & Trivedi, 2009, pg. 188), which weakens the significance of the results. We must therefore first test whether E_1 is exogenous. To do this, we compare the parameter estimates of the regular fixed effects estimation with those of an IV-FE estimation. In our case, the estimate for the impact of a new CEO in the first year equals -0.0765 using regular fixed effects (see Table 4.5) and -0.2073 (unreported) with IV-FE. We formally test whether there is a difference in these parameter estimates by applying the C statistic, which is a generalization of the Durbin-Wu-Hausman test in the sense that it allows for heteroskedasticity (Cameron & Trivedi, 2009, pp. 188–190; Hayashi, 2000, pp. 233–234). In our case, we are not able to reject the null that the coefficients are equal (p-value of 0.2049); hence, we cannot reject the null that the regressor is exogenous.[20] This result, combined with our earlier observation that cases resulting in reverse causality are unlikely to occur, significantly reduces our concerns about the problem of endogeneity.

4.6.3 Reason for CEO Turnover

Several possible explanations for the decrease in performance in the first two years after a change in CEO can be identified. It might be caused by a deterioration of net interest income or commissions or a spike in operating expenses. This, in turn, could be the result of a couple of factors: the new CEO might need time to get used to the bank, its people, and the local community, or they might simply be a worse executive than the old CEO. Bank performance could also drop as a result of an increase in the provisions for credit risks. Increasing provisions can be motivated by a difference in opinion between the new and the old CEOs regarding credit risk. Such increase can also be influenced by other factors, though, such as a need to offset a decrease in provisions taken in the final year of an exiting CEO, as part of a strategy to show increased performance prior to departure, or when a new CEO wants to take a so-called earnings bath (Bornemann

[20] We repeated these analyses where we also included the lagged effect, E_2 (Specification 3 of Table 4.5). The results were similar. The Kleibergen-Paap rk LM statistic rejects the null of weak instruments, with a p-value of 0.0000, while the p-value of the C statistic equals 0.2148.

et al., 2015). Bornemann et al. (2015) provide empirical evidence of this "big bath" theory for CEO changes at German savings banks. The initial poor performance at the bank is then implicitly ascribed to the previous CEO, and when performance rebounds in subsequent years, this is ascribed to the new CEO.

It is not possible to determine from the results presented in Table 4.5 above which of these explanations is the most likely determinant of performance variation. We therefore analyze each one separately to identify the most likely cause of decreased performance after CEO turnover. We first consider whether it is related to new CEOs being of lower quality than the departing CEOs by zooming in on the various reasons of departure.[21] Table 4.2 above contains an overview of the three main categories of departure: positive, neutral, and negative. The positive category is composed of CEOs that have been promoted, while the negative category contains dismissed or demoted CEOs. A departure is designated as neutral when a CEO leaves for reasons unrelated to performance or transfers to another local bank that is not significantly larger. In order to assess whether we find heterogeneous effects on performance for different reasons of departure, we estimate the following fixed effects regression model:

$$RoA_{it} = \alpha + \kappa_t + \sigma_i + \beta X_{it} + \sum\nolimits_{\tau=\{1,2\}} \sum\nolimits_{k\in\{+,=,-\}} \lambda_{\tau,k} E_\tau RD^k_{i,t} + \varepsilon_{it}, \tag{4.4}$$

where $RD^k_{i,t}$ is a dummy equal to 1 when a CEO leaves bank i with reason k in year $\boldsymbol{t-1}$. The reason for departure, k, can take on three values: positive (+), neutral (=), or negative (-). Hence, the three dummies, $RD^k_{i,t}$, allow us to evaluate the performance of the new CEO distinguishing between each reason for the predecessor's departure. In Table 4.6 we present the results for when only the first year of the new CEO is included, that is τ equals 1 (Specification 1) and when the new CEO's second year is added as well, that is τ equals 1 and 2 (Specification 2).

[21] In this setting, quality should be interpreted as attributes that are relevant for leading a local bank, cf. Jenter et al. (2016). This is the same as the use of "talent" in Gabaix and Landier (2008) and "managerial ability" in Terviö (2008).

Table 4.6. Results of the regular fixed effects (FE) model considering reasons for departure. Return on assets is the dependent variable, and the first year(s) of the new CEO multiplied by the reason for departure of the departing CEO are the main independent variables. We only include control variables that were significantly related to return on assets in Section 4.6.1. Time and bank fixed effects are included, and the error terms are clustered per bank. The p-values are reported in parentheses under the parameter estimates.

	(1)	(2)
$E_1 = 1 \times$ Reason=negative	-0.0342	-0.0701
	(0.538)	(0.244)
$E_1 = 1 \times$ Reason=neutral	-0.155**	-0.170**
	(0.036)	(0.022)
$E_1 = 1 \times$ Reason=positive	-0.0151	-0.0242
	(0.818)	(0.705)
$E_2 = 1 \times$ Reason=negative		-0.170***
		(0.004)
$E_2 = 1 \times$ Reason=neutral		-0.0577
		(0.380)
$E_2 = 1 \times$ Reason=positive		-0.0277
		(0.670)
Log(Assets)	-1.173***	-1.280***
	(0.009)	(0.003)
Equity to assets	-0.159***	-0.161***
	(0.000)	(0.000)
Observations	530	530

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We first focus our attention on the results of the first specification. Although the impact on performance is only significant in the second case (neutral), bank performance declines in the first year of a new CEO for all three causes of CEO turnover. In other words, the impact on bank performance is not positive in any of the cases. Even when CEOs are dismissed or demoted (see first line of the table) and it is most likely that a new CEO will improve upon the performance of their predecessor, the impact remains non-positive. We must, however, realize that CEOs could also be dismissed for reasons unrelated to financial performance, such as disagreement within the executive board or a lack of trust between the executive and supervisory boards. When a difference in quality between the old and new CEOs is the presumed explanation for the overall finding of a decline in performance, we would have expected the largest decline in performance to be in cases where a CEO has been promoted (line three). This is not what we find: the impact on performance in these cases is almost equal to 0. On the other hand, when the reason for departure is neutral (line two), the decline in performance is statistically significant at the 5% level. Differences in quality between the predecessor and successor would explain this result only in cases where the successors were systematically worse than the predecessors.

The results in the second specification are similar to those of the first specification for the first year of the new CEO. Moreover, the impact on performance in the second year is once again non-positive for all three causes of departure. However, in contrast to the neutral category in the first year, the cases where the former CEO has been dismissed or demoted (line four) now drive the overall negative impact on bank performance (see Specification 3 of Table 4.5). This result would only be consistent with the difference-in-quality explanation if the new CEOs were systematically worse than the old CEOs who left for a negative reason. Finally, and in line with the results for the first year, the negative impact on performance is smallest in cases where the former CEO was promoted, which is the opposite of what we would have expected if differences in CEO quality were the driving force behind the results.

In order to assess how departing CEOs performed in their last year, and whether this might explain the change in performance in the first year of the new CEO, we estimate the following model:

$$RoA_{it} = \alpha + \kappa_t + \sigma_i + \beta X_{it} + \sum\nolimits_{k \in \{+,=,-\}} \lambda_k E_0 RD^k_{i,t} + \varepsilon_{it}, \tag{4.5}$$

which is the same as Equation (4.4), except that we now focus on the last year of the old CEO, E_0. Since the attention is shifted to the departing CEO, we use the predecessor file for this analysis (see Section 4.4.3).[22] Results are presented in Table 4.7.

Table 4.7. Results of the regular fixed effects (FE) model considering reasons for departure. Return on assets is the dependent variable and the last year of the departing CEO multiplied by the reason for departure of the departing CEO are the main independent variables. We only include control variables that were significantly related to return on assets in Section 4.6.1. Time and bank fixed effects are included, and the error terms are clustered per bank. The p-values are reported in parentheses under the parameter estimates.

	(1)
$E_0 = 1 \times$ Reason=negative	-0.0320
	(0.611)
$E_0 = 1 \times$ Reason=neutral	-0.0580
	(0.246)
$E_0 = 1 \times$ Reason=positive	0.0633
	(0.142)
Log(Assets)	-1.105**
	(0.012)
Equity to assets	-0.152***
	(0.000)
Observations	530

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We do not document a statistically significant difference in performance in the final year of a former CEO's tenure for any of the reasons of departure. Moreover, when we test whether the coefficients pertaining to the three reasons of departure are jointly equal to 0, we cannot reject this null (p-value of 0.2602). We discuss the implications of these results separately for each of the three categories below.

[22]In 10 instances, 2015 was the last year of a departing CEO. Since 2015 was the last year of our data, these cases are irrelevant for the analyses related to the first year(s) of a new CEO. For the analyses related to the last year of an exiting CEO, however, they have been included.

It appears that CEOs who were dismissed or demoted (first line) were not significantly underperforming. As suggested above, other considerations than financial performance might have played a role in these cases. Moreover, they were also not outperforming, which makes it unlikely that the outperformance in the second year of a new CEO (see Specification 2 of Table 4.6) can be explained by a difference in quality. CEOs who left due to a neutral reason (second line) neither underperform nor outperform in their final year. This renders it unlikely that a difference in quality between predecessor and successor explains the results for the neutral category in the first year of Table 4.6, because in that case we would have expected a significant outperformance (and not a slight underperformance) in the final year of the predecessor (see Table 4.7). Finally, although insignificant, CEOs who were promoted show the strongest performance in the year before departure. The difference-in-quality explanation would then prescribe the strongest decline in performance in the first years of the new CEO for such cases, which is the exact opposite of what we have documented in Table 4.6. This thus undermines the difference-in-quality explanation even further. We must therefore turn to other possible explanations for the decline in performance.

4.6.4 Cause of Low Performance after CEO Turnover

Three other possible explanations for the negative performance in the first year(s) of a new CEO remain. The first is a decline in performance because the new CEO has to acclimate and become accustomed to the new bank; the second is a decline because the new CEO decides to take an earnings bath; and the third is the need of the new CEO to catch up on a backlog in provisions built up during the tenure of the former CEO. To find the explanation, we analyze the underlying factors causing the drop in return on assets.

The return on assets equals the net earnings of a local bank divided by the average of assets at the beginning and end of the year. Net earnings, in its turn, can be decomposed as follows:

$$\text{net earnings} = \text{net int inc} + \text{commissions - oper exp - } \Delta \text{ provisions - tax,}^{23} \quad (4.6)$$

where net int inc is equal to the interest income on company and retail loans minus interest costs on deposits and funding from the central organization. Commissions represents other forms of income, such as compensation for maintaining the payments system or up-front amounts when loans are granted. The other three entries are deducted from this total income. Operating expenses are non-interest expenses of the local bank, such as labor, administration, and maintenance costs. Δ provisions is the net amount reserved in a year to cover impaired loans.

When classifying loans as impaired and taking provisions for these impairments, banks act in accordance with the following rules: a loan is classified as impaired when either the interest payments are 90 days behind schedule or when the bank deems it likely that a borrower will be unable to honor its obligations. If a loan is classified as impaired, the size of the provision equals the difference between the book value of the loan and the estimated net present value of future cash flows, which is based on assumptions. These provisions are subsequently recognized in the profit and loss account and hence an increase lowers the bank's profits.[24] Finally, tax is subtracted, which in general represents a fraction of net earnings before taxes.

Table 4.8 shows the regression results for return on assets (Specification 1) and each of its five constituent factors (Specifications 2 to 6) as dependent variables.[25]

[23] We exclude two components – proceeds from companies a local bank invested in and other earnings – since these comprise only 0.15% of total income.

[24] Information about impaired loans and provisions was obtained from the bank's annual report. Since we are not allowed to disclose the name of the bank, we cannot refer to the exact sources.

[25] Note that when we use the constituent factors as dependent variables they are also divided by average assets. For example, in Specification 1 of Table 4.8, this implies that net int inc to average assets is the dependent variable. In the discussion of the results we only refer to the numerator and we do not state "average assets."

Table 4.8. Results of the regular fixed effects (FE) model with return on assets and its constituents (net int inc to assets, commissions to assets, etc.) as dependent variables. A dummy indicating the first year of the new CEO, E_1, is the independent variable of interest in panel A, and two dummies indicating the first two years of the new CEO, E_1 and E_2, are the independent variables of interest in panel B. We only include control variables that were significantly related to return on assets in Section 4.6.1. Time and bank fixed effects are included, and the error terms are clustered per bank. The p-values are reported in parentheses under the parameter estimates.

Panel A: First year of new CEO

	RoA (1)	net int inc (2)	comm (3)	oper exp (4)	Δ prov (5)	tax (6)
E_1	-0.0765*	-0.00499	-0.00507*	0.00950	0.0834*	-0.0251*
	(0.058)	(0.628)	(0.075)	(0.509)	(0.098)	(0.062)
Log(Assets)	-1.140**	-0.286	-0.259***	-0.0453	1.013**	-0.407***
	(0.010)	(0.364)	(0.000)	(0.861)	(0.049)	(0.005)
Equity to assets	-0.156***	-0.00317	-0.00536	0.0575**	0.142***	-0.0543***
	(0.000)	(0.847)	(0.241)	(0.012)	(0.004)	(0.000)
Observations	530	530	530	530	530	530

Panel B: First two years of new CEO

	RoA (1)	net int inc (2)	comm (3)	oper exp (4)	Δ prov (5)	tax (6)
E_1	-0.0950**	-0.0109	-0.00578*	0.0139	0.0973**	-0.0312**
	(0.019)	(0.361)	(0.073)	(0.396)	(0.048)	(0.022)
E_2	-0.0768**	-0.0247*	-0.00295	0.0184	0.0577	-0.0252*
	(0.048)	(0.099)	(0.340)	(0.365)	(0.216)	(0.055)
Log(Assets)	-1.156***	-0.291	-0.259***	-0.0414	1.025**	-0.412***
	(0.009)	(0.355)	(0.000)	(0.872)	(0.045)	(0.004)
Equity to assets	-0.154***	-0.00258	-0.00529	0.0571**	0.140***	-0.0537***
	(0.000)	(0.875)	(0.245)	(0.012)	(0.004)	(0.000)
Observations	530	530	530	530	530	530

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We first discuss the results of Panel A, where only the dummy for the first year of the new CEO is included. Then we will move on to the results of Panel B, where the lagged effect has also been added. The first specification in Panel A shows our earlier result of underperformance at a bank in the first year of a new CEO. This decline in return on assets cannot be attributed to a decrease in net interest income or an increase in operating expenses (see Specifications 2 and 4, respectively). The decrease in return on assets is almost entirely explained by an increase in provisions (Specification 5).[26] Although commissions also show a significant decrease (Specification 3), the economic impact on return on assets is negligible, compared to the impact of Δ provisions. The results for the first year of a new CEO in Panel B are similar, but statistically stronger than the results in Panel A. In the second year, the return on assets again shows a significant decline. Although the decrease in net interest income is significant at the 10% level, the decline in return on assets is again, for the largest part, caused by an increase in provisions (even though the coefficient is statistically insignificant).

These results are in line with the finding of Jenter et al. (2016) that CEO turnover has no impact on operating performance. They also undermine the argument that a new CEO needs time to adapt and become acquainted with their new bank, for in such a case, we would have expected a decrease in performance due to a material decline in income or an increase in costs. Here, however, the decline in performance is almost entirely caused by the increase in provisions for impaired loans, which is in line with the finding of Bornemann et al. (2015) for German savings banks. This evidence suggests that in their first year(s) in power, a new CEO classifies additional loans as impaired and takes corresponding provisions to cover for expected losses. The final, sixth specification indicates a significant decline in tax expenditure. This, however, is merely a mechanical effect, since taxes automatically decline when earnings do.

The increase in provisions can be interpreted in the following two ways: *departing* CEOs have been too lenient in provisioning for non-performing loans or *new* CEOs take

[26] We also want to check whether the decrease in return on assets and the increase in provisions can be explained by a new CEO bringing in new clients. Therefore, in unreported regressions, we have added asset growth as independent variable to Specifications 1 and 5 in the table above. Asset growth has been chosen instead of loan growth since loans comprise 92% of the median bank's assets. The results do not materially change compared to the baseline specifications.

an earnings bath in their first year. If the increase were due to departing CEOs being too lenient, we would expect a negative relationship between the dummy in the last year(s) of the departing CEO, E_{-1} and/or E_0, and Δ provisions. If, on the other hand, it is due to CEOs taking an earnings bath, we expect the coefficient on dummies in subsequent years to reverse. Therefore, we estimate regressions with Δ provisions to assets as the dependent variable and dummies equaling 1 in the last two years of the old CEO and the first three years of the new CEO as main independent variables. Results are presented in Table 4.9.

Table 4.9. Results of the regular fixed effects (FE) fixed effects model with Δ provisions to assets as the dependent variable and E_τ for $\tau \in \{-1, 0, 1, 2, 3\}$ as the main independent variables. We only include control variables that were significantly related to return on assets in Section 4.6.1. Time and bank fixed effects are included, and the error terms are clustered per bank. The p-values are reported in parentheses under the parameter estimates.

	$\tau = -1$	$\tau = 0$	$\tau = 1$	$\tau = 2$	$\tau = 3$
E_τ	-0.135**	0.0300	0.0834*	0.0284	-0.0681*
	(0.018)	(0.439)	(0.098)	(0.558)	(0.060)
Log(Assets)	0.970*	0.982*	1.013**	0.983*	0.963*
	(0.058)	(0.057)	(0.049)	(0.053)	(0.060)
Equity to assets	0.129***	0.141***	0.142***	0.141***	0.143***
	(0.006)	(0.003)	(0.004)	(0.003)	(0.003)
Observations	530	530	530	530	530

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

For $\tau = 1$, the results are identical to the fifth specification in Panel A of Table 4.8: that is, in the first year of the new CEO, there is a significant increase in provisions for impaired loans. The insignificance of the dummy's coefficient when $\tau = 0$, representing the last year of the departing CEO, shows that they were not more lenient in classifying impaired loans in their final year. However, when we go back another year ($\tau = -1$), the second-to-last year of the predecessor, we do document a significant decline in provisions. In unreported regressions, we found that this decline in provisions is paired with an increase of similar size in return on assets in the second-to-last year.

Next, we assess whether the increase in Δ provisions in the first year is reversed in subsequent years. For the second year of a new CEO ($\tau = 2$), we document an insignificant and slightly positive impact on provisions. A reversal takes place in the third year ($\tau = 3$), when provisions are significantly decreased by an almost equal amount as the increase in the first year.

In sum, the increase in provisions in the first year of the successor occurs two years after *and* two years before a significant decline in provisions. Therefore, the increase in provisions in the first year of the new CEO seems to be induced by two forces. On the one hand, it is the flipside of the decrease in provisions two years before the changeover, and on the other, the new CEO takes an earnings bath which is subsequently offset in the third year.[27]

4.7 Conclusion

The goal of this chapter is to establish the impact of CEO turnover on the financial performance of banks. We documented that in the first year(s) of a new CEO, a bank's financial performance drops significantly. The return on assets decreases with 0.08 percentage points in the first year and 0.17 percentage points in the first two years, which equals 23% and 50% of the standard deviation, respectively. This decline is not a consequence of lagging interest income, a decrease in commissions, or a surge in operating expenses, but can be attributed to an increase in provisions for impaired loans. The *increase* in provisions in the first year of a newly appointed CEO is paired with a *decrease* in provisions in the second-to-last year of the old CEO and in the third year of the new

[27] We remark that the combination of an increase in provisions in the first year of a new CEO, and subsequently, a reversal in the third year, need not be a reflection of opportunistic behavior per se. An alternative interpretation could be that the new CEO wants to ensure that they will not be confronted with unforeseen bad loans in the future. Therefore, the successor increases the provisions in the first year, and, subsequently, when they become familiarized with the loan book, may discover that the initial provisions were too conservative, which then leads to a decrease in these provisions.

CEO.

We conclude from this that in their first year, a successor CEO wants to offset the backlog in provisions inherited from their predecessor and/or ensure a position from which to boost results – by decreasing provisions in the future. The decrease in performance due to an increase in provisions is not without harm. Losses at banks reduce their capital position and inhibit their ability to extend credit to customers. In addition to these indirect effects, clients whose loans have been classified as impaired will become subject to increased scrutiny from the bank, which might lead to additional costs for both customer and bank.

5 | The World We Live In: Global or Local?

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Abstract

In this chapter, we document economically *and* statistically large differences in the cost of equity by comparing a global CAPM to a local CAPM. We consider fifteen countries over a nearly 20-year period (1996–2015). While the application of the global version of the CAPM in cases where a global market index is used as a pricing factor would seem justified by increased capital market integration, the empirical evidence on this has been inconclusive to date. We found that the average difference in the cost of equity between the models was equal to 0.77 percentage points, which represents about 20% of the historical risk premium. Moreover, for almost 20% of the companies, this difference in cost of equity is also statistically significant. For these companies the difference in cost of equity is equal to 1.49 percentage points. We therefore conclude that not applying the global CAPM but instead the local CAPM can lead to considerable mistakes in cost-of-equity calculations.

5.1 Introduction

An important element in determining the cost of equity for individual companies is the capital asset pricing model (CAPM). In theory, the global version of the model, the ICAPM, should be used for integrated financial markets, since integration implies that stocks are priced similarly across the board, irrespective of where they are traded. That would make the global market index the most relevant index, and it should therefore replace the local indices used for cost of capital calculations in the traditional local CAPM. The underlying empirical results have, however, been inconclusive to date.

This chapter presents an analysis of the cost of equity in global financial markets. It builds on Koedijk, Kool, Schotman, and Van Dijk (2002) and Stulz (1995) in the sense that it assesses whether there is a pricing error in the computation of the cost of equity when a local CAPM is used even though the ICAPM applies. This pricing error is especially interesting from a practical point of view, since the CAPM is still the benchmark model in practice for calculating the cost of equity.[1] The widespread use of the CAPM has been demonstrated by Graham and Harvey (2001) for the U.S. and Brounen, De Jong, and Koedijk (2004) for Europe.

This chapter uses the same methodology as Solnik (1974b) and Stulz (1995). Solnik (1974b) reviewed nearly 300 stocks from nine developed countries and found a difference in the cost of equity when the local CAPM was used despite the fact that the ICAPM applied for more than 50% of the companies. Stulz (1995) took this into greater detail, limiting his analysis to Nestlé, and documented an economically large difference. In Koedijk et al. (2002), the approach of Solnik (1974b) and Stulz (1995) was extended by

[1] Acquaintances working for international investment banks told us that the CAPM is still the benchmark model for computing the cost of equity. At one bank, they always use the local CAPM model, and at another, it depends on whether the company in question operates primarily locally or globally. For companies operating globally, the cost of equity is then computed with a global version of CAPM. Finally, investment banks often use Damodaran data sets (`http://pages.stern.nyu.edu/~adamodar/`) to find a company's beta. The definitions for the variables in those data sets state that the beta is computed using a local CAPM, where the index is "the most widely followed index in the market."

adding exchange rates as pricing factors in the model. Their sample consisted of 3,293 stocks in nine countries. Overall, Koedijk et al. (2002) found that for many companies in their sample, it did not matter whether the global or local CAPM was used. Applying an alternative method and focusing exclusively on the U.S., Harris, Marston, Mishra, and O'Brien (2003) also concluded that it did not matter much for the cost-of-equity computation whether the local or global market model was used. Moreover, Jacquillat and Solnik (1978) had previously concluded that adding other major markets on top of the home market often does not yield any improvement in explaining the stock returns of multinational firms. While this result is consistent with the findings of Koedijk et al. (2002), it must be treated with care, since the developed markets at the time were not yet integrated.

In sum, the empirical evidence thus far has been inconclusive. The culmination of capital market integration in developed countries in the 1990s (Bekaert, Harvey, Lundblad, & Siegel, 2011), which is a basic assumption in our model, presents us with a 20-year time period for assessing the impact on the cost of equity of using a local instead of a global model. Moreover, the increasing capital market integration of emerging markets (Bekaert & Harvey, 2003; Carrieri, Chaieb, & Errunza, 2013) justifies extending the analysis to emerging markets. Our results show that over the entire period we focus primarily on, 1996–2015, the difference in cost of equity when using the local CAPM despite applicability of the ICAPM was equal to 0.77 percentage points. This represents 18% of the historical risk premium.[2] Moreover, on average for 19% of the companies in a country, this difference is also statistically significantly distinct from zero. Furthermore, this percentage differs considerably between countries, ranging from 1.9% for China to 63% for Switzerland. When focusing exclusively on companies for which the difference is significantly different from zero the mistake in cost of equity jumps from 0.77 to 1.49 percentage points – equal to 35% of the historical risk premium. This implies that not

[2]The equity risk premium for a U.S. investor on the global market for the period 1900-2015 is equal to 4.2% (Credit Suisse, 2016, pg. 61). Therefore, a mistake in cost of equity of 0.77 percentage points represents 0.77%/4.2%=18% of the global equity risk premium.

using the ICAPM but instead the local CAPM in cost of equity calculations can lead to considerable mistakes.

The previous discussion does not distinguish between an under- and overestimation of the cost of equity. The implications are, however, the exact opposite. Using the Gordon growth model, where the stock price represents the discounted stream of future dividends and the discount rate equals the 'real' cost of equity (Gordon, 1962; Gordon & Shapiro, 1956; Williams, 1938), any underestimation of the cost of equity implies an overvaluation of the company. This, in turn, could result in overinvestment by that company. In our sample, this situation occurs in Switzerland. Conversely, overestimation of the cost of equity leads to the undervaluation of a company.

For fourteen of the fifteen countries we considered, it made a difference for at least 5% of the sample companies whether the ICAPM or local CAPM was used. Remarkably, this was not the case for China, where only 1.9% of the sample companies had errors that were significantly different from zero. We ascribe this to the segmentation of the Chinese capital market in general and the overrepresentation in our sample of small Chinese stocks, which are particularly likely to be more segmented.

As a robustness check we extended the global pricing model by adding the Fama-French factors. Since we only have data on the Fama-French factors for North America and Europe, we could not perform this analysis for all countries. However, for the majority of the countries for which we did have that data, there is a slight increase in the number of companies for which the cost of equity differs significantly when the local model is used even though the global model applies when that data is added in. Therefore, we conclude that our results are robust for this more general specification.

The chapter proceeds as follows. Section 5.2 discusses the integration of capital markets. In Section 5.3, we explain our methodology, while Section 5.4 describes the data. In Section 5.5, we present the results and in Section 5.6, we show the robustness of our results for an alternative model. Finally, we present our conclusions in Section 5.7.

5.2 Capital Market Integration and the Cost of Equity

Stulz (1995) assumes integration of capital markets throughout his analysis of the difference in cost of equity when using a local versus a global market index. He argues that the internationalization of capital markets has made the use of the local CAPM inappropriate, especially for small countries. In the twenty years that have passed since Stulz published his findings, the globalization of the world economy has only accelerated, as reflected for instance by the increasing prominence of emerging markets in the world.

There is much academic research focusing on market integration in general and the developments in the emerging markets in particular. According to Bekaert et al. (2011), the local markets of developed countries were integrated with global markets as of 1993, although emerging markets are still segmented. This segmentation persists despite an increase in capital flows to emerging markets throughout the 1990s (Bekaert & Harvey, 2003). The authors link this increase in capital flows to the liberalization of capital markets in emerging markets.

Carrieri et al. (2013) start with a theoretical approach to integration, which was developed by Errunza and Losq (1985), drawing a distinction first between integrated and segmented markets and subsequently within segmented markets between accessible and non-accessible securities. The former are securities in which international investors can invest, while the latter are isolated from international investors. Markets with securities shielded from foreign investors are not fully integrated with world capital markets. Therefore, these segmented securities have a global market risk premium and a local risk premium, whereas integrated securities only have a global risk premium. An example of such a situation is China, where A shares are only available to domestic investors, while B shares can be acquired by both domestic and foreign investors.

When they compare their model with the data, Carrieri et al. (2013) show that the markets of developed economies are integrated with global capital markets. Furthermore, in emerging markets, stocks that are accessible to all investors are integrated with capital markets and hence only have global market risk. However, stocks that are not accessible to all investors have not only global market risk, but also local market risk. Whether emerging markets in the aggregate are characterized more as integrated or segmented then depends on the relative importance of accessible versus non-accessible stocks. Nevertheless, there appears to be consensus that the segmentation of emerging markets is decreasing over time (Bekaert & Harvey, 2003; Carrieri et al., 2013).

Despite evidence that capital markets are becoming increasingly integrated, there are still barriers to integration. Bekaert and Harvey (2003) distinguish between three types of barriers: legal, indirect, and emerging-market specific. Legal barriers make it difficult or unattractive for foreign investors to invest in a country. These include such things as restrictions on foreign ownership or additional taxes for foreigners. Indirect barriers refer to differences in the level of information available to domestic and foreign investors, unfamiliar accounting standards, and limited protection for small investors. This is corroborated by Carrieri et al. (2013), who point specifically to the quality of information, the institutional environment, and corporate governance standards as factors hindering the integration of emerging markets. A theoretical exposition of how the expropriation of outsiders (including foreign investors) by corporate insiders and sovereign states leads to segmentation is provided by Stulz (2005). Finally, emerging markets have specific risks related to liquidity, politics, and economic policy. In sum, it is safe to assume that financial market integration is justifiable for developed countries. For emerging markets, however, although they are increasingly integrated with world capital markets, there still remain barriers to integration. This should be kept in mind when we interpret our empirical results.

5.3 Methodology

Similar to Stulz (1995), we use the CAPM of Grauer, Litzenberger, and Stehle (1976), in which the market factor is the only factor in the asset pricing model. In this model, purchasing power parity is assumed [or deviations are not large enough to impact asset prices (Stulz, 1995)] and therefore exchange rate risk is not priced. It is possible to extend the model to the Solnik-Sercu model (Sercu, 1980; Solnik, 1974a), which allows for exchange rate risk to be priced. For our purposes, however, since it is unclear whether exchange rate risk is priced or not (Bekaert & Hodrick, 2009, p. 451), we will use the simple CAPM model.[3]

In deriving our testable hypothesis we follow the set-up of Koedijk et al. (2002) and Stulz (1995). Let R_i be a vector of length T of total returns in U.S. dollars on individual stocks $i \in \{1, ..., N\}$. R_G is a vector of length T of total returns on a global equity market index, measured in U.S. dollars. The ICAPM can be written as

$$E[R_i] = \alpha_{G,i} + \beta_{G,i} E[R_G], \tag{5.1}$$

where $\beta_{G,i} = \frac{Cov[R_i, R_G]}{Var[R_G]}$ (e.g., Bekaert & Hodrick, 2009, pp. 446–447). Since we assume integration of capital markets, this is the correct model to compute the cost of equity. We choose the CAPM representation that includes the riskless interest rates in the $\alpha_{G,i}$ term. This representation of asset prices is the maintained hypothesis throughout the chapter.

The local CAPM model is similar to Equation (5.1), with the global equity market

[3]Dumas and Solnik (1995) show that the exchange rate risk for Germany, the U.K., Japan, and the U.S. is priced, while Griffin and Stulz (2001) conclude that exchange rate shocks have only a small impact on stock returns. For an excellent overview of alternative asset pricing models in global financial markets, we refer readers to Karolyi and Stulz (2003).

index replaced by a local one, written as R_L. The local CAPM is given by

$$E[R_i] = \alpha_{L,i} + \beta_{L,i} E[R_L],$$

where $\beta_{L,i} = \frac{Cov[R_i, R_L]}{Var[R_L]}$ and $\alpha_{L,i}$ incorporates the riskless rates terms. This would be the correct model to determine the cost of equity if capital markets would have been *segmented*. However, even though we assume *integrated* markets, the local CAPM does not necessarily lead to a significant difference in cost of equity compared to the ICAPM. The main goal of this chapter is to determine when this difference is significant. In the remainder of this section, we will derive a testable hypothesis to test the significance of this difference.

Since $\beta_{G,i}$ and $\beta_{L,i}$ coincide with the regression coefficients of regressing R_i on R_G and R_L, respectively, we can write

$$R_i = \alpha_{G,i} + \beta_{G,i} R_G + \varepsilon_{G,i}, \tag{5.2}$$

and

$$R_i = \alpha_{L,i} + \beta_{L,i} R_L + \varepsilon_{L,i}, \tag{5.3}$$

where $\varepsilon_{G,i}$ and $\varepsilon_{L,i}$ have mean zero and are orthogonal to R_G and R_L, respectively (see Appendix A.1 for a derivation of the orthogonality between $\varepsilon_{G,i}$ and R_G).

Given that the ICAPM is the maintened hypothesis throughout the chapter, it should also hold for the return on the local index, R_L; that is,

$$\mathrm{E}[R_L] = \alpha_{G,L} + \beta_{G,L} \mathrm{E}[R_G].$$

Similar to Equations (5.2) and (5.3), we obtain:

$$R_L = \alpha_{G,L} + \beta_{G,L} R_G + \varepsilon_{G,L}, \tag{5.4}$$

where $\varepsilon_{G,L}$ has mean zero and is orthogonal to R_G.

Inserting this expression into Equation (5.3), we get

$$R_i = \alpha_{L,i} + \beta_{L,i}\left(\alpha_{G,L} + \beta_{G,L}R_G + \varepsilon_{G,L}\right) + \varepsilon_{L,i}$$
$$= \alpha_{L,i} + \beta_{L,i}\alpha_{G,L} + \beta_{L,i}\beta_{G,L}R_G + \beta_{L,i}\varepsilon_{G,L} + \varepsilon_{L,i}. \quad (5.5)$$

If the ICAPM holds, $\varepsilon_{G,L}$ is orthogonal to R_G and Equations (5.2) and (5.5) are equivalent if and only if local idiosyncratic risk $\varepsilon_{L,i}$ is orthogonal to R_G. In that case, the parameters of Equations (5.2) and (5.5) corresponding to the risk factors should be equal, such that

$$\beta_{G,i} = \beta_{L,i}\beta_{G,L}. \quad (5.6)$$

To test for orthogonality between $\varepsilon_{L,i}$ and R_G, we consider the following regression equation:

$$\varepsilon_{L,i} = \kappa_i R_G + \eta_i, \quad (5.7)$$

where κ_i is the parameter for the global index, and η_i has mean zero and is orthogonal to R_G and R_L. In the bivariate case with only one independent variable, the regression anatomy formula presented in Angrist and Pischke (2009, pg. 27), which they ascribe to Frisch and Waugh (1933), implies:

$$\kappa_i = \frac{Cov[\varepsilon_{L,i}, R_G]}{Var[R_G]} = \frac{E[\varepsilon'_{L,i} \cdot R_G]}{Var[R_G]},$$

where the second equality holds because $E[\varepsilon_{L,i}] = 0$. Our null hypothesis then is that the part of the return not accounted for by the local index (i.e., $\varepsilon_{L,i}$) is orthogonal to the global index. In other words, the global index cannot explain the return development of asset i any better than the local index. This would imply that no error is made by using the local CAPM instead of the ICAPM, and thus the pricing error equals zero.

To test for differences in the cost of equity when using the local versus the global index, we insert Equation (5.7) in Equation (5.3) to arrive at

$$R_i = \alpha_{L,i} + \beta_{L,i} R_L + \kappa_i R_G + \eta_i, \tag{5.8}$$

where η_i has mean zero and is orthogonal to R_G and R_L (see Appendix A.2 for a derivation of this result). This equation is similar to Equation (8) of Koedijk et al. (2002). We use a t-test to test at the 5% level whether the coefficient for the global index, κ_i, is equal to zero. This will be tested per company.[4]

The derivations above are based on the assumption that capital markets are fully integrated. At the end of Section 5.2, we concluded that this is a valid assumption for developed countries but not for developing ones. Caution is therefore advised in applying the aforementioned framework to emerging markets. Intuitively, the more segmented markets are, the more important local factors will be in explaining a firm's stock return, and hence the more likely it will be that the global factors will not add much information. Therefore, the local factor, R_L, will explain much of the firm's stock return for a company segmented from world markets. This implies that the global factor, R_G, will be less relevant and hence the corresponding coefficient κ_i will often be close to zero. The results are presented and discussed later in the chapter, where we focus first on the statistical significance of the difference between using the local CAPM versus the ICAPM (Section 5.5.1), before assessing whether this difference is also economically significant (Section 5.5.2).

5.4 Data

In our sample, we consider the world's thirteen largest economies (not including Italy), plus the Netherlands and Switzerland. Italy was left out of the sample because we did not have access to the index constituents of the past, and the latter two countries were included because Dutch and Swiss multinational companies sell a large share of their

[4]This set-up assumes that the sample companies are independent observations. An interesting extension of this approach would be to allow for correlation between stock returns of the companies.

products abroad (Jacquillat & Solnik, 1978), which is an interesting setting to test our hypothesis. This amounts, then, to eleven developed countries and the BRIC (Brazil, Russia, India, and China) countries. The starting point for the selection process in choosing the companies per country was the major index in that country, where we identified all of the constituents (i.e., every company that appeared at least once in the index from 1980 to 2015) and used this as our sample of firms.[5] In addition to our sample of firms, we also collected data on the local market indices from the sample countries and the global market index.[6] Share prices and market indices are recorded at a monthly frequency from Datastream, and dividends are reinvested. In the rest of the chapter, we focus on the period from January 1996 to June 2015. Our time period starts a few years after developed markets were considered fully integrated with global markets [i.e., 1993, the date given by Bekaert et al. (2011)]. A complete overview of the data and the sources can be found in Appendix B.

At this point, it is important to mention that throughout this chapter, we adopt the perspective of a U.S. investor. Consistency therefore requires that all returns be converted into U.S. dollar returns. It was not possible, however, to download the local MSCI index for Russia or China in U.S. dollars. To overcome this problem, we converted both of these indices, which were initially denominated in the local currencies, into U.S. dollar amounts using exchange rate data from Datastream (Russia) and FRED[7] (China).

Table 5.1 contains an overview of the stocks in our sample.

[5] For Australia, we could only download the constituents for May and June 2015.

[6] The local market for Russia starts on May 1, 1996.

[7] Federal Reserve Economic Data, Federal Reserve Bank of Saint Louis, `https://research.stlouisfed.org/fred2/`.

Table 5.1. The second column contains the number of companies per country in the raw dataset that had at least one observation in the period 1996–2015. Columns 3, 4, and 5 contain the number of companies listed for the periods 1996–2015, 1996–2005, and 2006–2015, respectively. In the third to fifth columns, companies have been excluded for which one of the following applies: 1) there are not at least 12 observations; 2) stock returns are equal to zero for more than 20% of the observations; or 3) the average annual return is over 200%.

Country	# sample stocks	# sample stocks 1996–2015	# sample stocks 1996–2005	# sample stocks 2006–2015
Australia	332	326	272	266
Canada	538	530	443	474
France	242	238	207	192
Germany	1,010	985	857	780
Japan	209	207	195	205
The Netherlands	58	57	47	52
Spain	71	69	58	63
South Korea	200	114	82	132
Switzerland	76	76	66	76
United Kingdom	1,869	1,819	1,570	1,122
United States	1,033	1,013	954	774
Brazil	111	109	69	109
Russia	90	88	30	89
India	74	74	62	74
China	1,706	1,603	567	1,596
Total	7,657	7,345	5,509	6,041

In Column 2, we report the number of stocks per country, as determined by taking all of the companies included in the country's major stock exchange (see Column 2 of Table B.1 for these indices) between 1980 and 2015 that have also had at least one stock return in the period 1996–2015.[8]

Next, following Koedijk et al. (2002), we imposed the following restrictions on this

[8]In the first step, we used the constituents of the index to identify companies that had at one point been listed from 1980 to 2015. We then excluded companies which had been delisted before the start of our sample period, i.e., 1996. For example, a company which was in the index in 1985 but delisted in 1988 was excluded from the sample, whereas one that was in the index in 1985 but delisted in 1997 was included.

raw dataset. First, we required that there be at least twelve monthly observations for each company. Second, over the period for which the stocks are listed, each company must have had fewer than 20% zero-return observations. Third, the average annual return must not exceed 200%.[9] The number of companies satisfying these conditions is shown in Column 3 of Table 5.1.

In Columns 4 and 5, we restrict the full sample to stocks that had a listing in 1996–2005 and 2005–2015, respectively. The number of companies in Columns 4 and 5 is lower or equal to the number in Column 3 as a result of delistings and new listings from 1996 to 2015. The restrictions mentioned previously were also applied to the two 10-year sub-periods.

We point to two patterns in Table 1. First, there were many new listings in the BRIC countries from 1996 to 2015. This can be inferred from the difference between Columns 3 and 4. Moreover, only a few companies were delisted in this period, as inferred from the difference between Column 5 and Column 3.[10] This is a reflection of the development of these countries' capital markets in this period.

Second, for the developed economies, a considerable number of companies were delisted during the first sub-period. This is particularly true for the U.K. and the U.S., where 38% and 23%, respectively, of the companies listed at one point during the 1996–2015 period were delisted. This is confirmed by the World Development Indicators (WDI) from the World Bank (see `http://data.worldbank.org/indicator/CM.MKT.LDOM.NO?view=chart`), which show a peak in listings in 1996 for the U.S. and in 2006 for the U.K.[11]

[9] To arrive at the average annual return, we took the monthly mean return plus one to the power of twelve minus one, $R_{annual} = (1 + \bar{R}_{month})^{12} - 1$. In cases where this number exceeded 2 (200%), the company was excluded from the sample.

[10] A comparison of these columns does not give an exact number of new listings and delistings, due to the restrictions applied on each individual period.

[11] For a discussion about the reasons why the U.S. lags behind in terms of company listings, see Doidge, Karolyi, and Stulz (2017).

5.5 Results

The results section comprises three subsections. We first test whether there are statistically significant differences in the cost of equity when we use the local CAPM even though the ICAPM applies. Next, we assess how large the differences in the cost-of-equity levels are, whereby we make a distinction between companies with or without a statistically significant different cost of equity. Finally, we graphically depict the differences.

5.5.1 Difference in Cost of Equity

In this section, we assess whether the cost of equity differs significantly when we use the ICAPM versus the local CAPM. In Table 5.2, we present the rejection rates per country. Rejection takes place for company i when κ_i from Equation (5.8) is significantly different from zero. This means that in these cases, the cost of equity using the ICAPM is significantly different from that when using the local CAPM. The rejection rate is the number of sample companies in a country for which the null is rejected in relation to the total number of sample companies in that same country. For each country, we consider the full time period, 1996–2015, and the two sub-periods, 1996–2005 and 2006–2015, which both cover 10 years. In estimating the regression equations, we account for heteroskedasticity.[12]

[12] Since our data is on a monthly frequency, autocorrelation is less of a concern.

Table 5.2. The percentage of rejection compared to the total number of companies in our sample per country per time period. Rejection occurs when the coefficient of the global market in Equation (5.8) is significantly (at the 5% level) different from zero. A t-test is applied to test this hypothesis.

	1996–2015	1996–2005	2006–2015
Australia	17%	14%	16%
Canada	24%	11%	25%
France	11%	8.7%	14%
Germany	10%	10%	7.4%
Japan	34%	27%	26%
The Netherlands	26%	17%	21%
South Korea	7%	7.3%	16%
Spain	19%	14%	24%
Switzerland	63%	42%	49%
United Kingdom	19%	20%	15%
United States	15%	14%	15%
Brazil	22%	7.3%	19%
Russia	11%	0%	11%
India	11%	6.5%	18%
China	1.9%	3.2%	2.4%

First, focusing on the full period, we conclude that of the developed countries all have rejection rates above 5%. This means that the cost of equity changes significantly when the local CAPM is used despite applicability of the ICAPM for 7% to 63% of companies depending on the country. The most extreme case is Switzerland, where 63% of the companies in the full period show a significant difference in the cost of equity. This is consistent with the results of Jacquillat and Solnik (1978), who document a large increase in explaining Swiss stock returns when other market indices are added to the Swiss index. In sum, we conclude that whether or not the local CAPM is used even though the ICAPM applies often makes a difference in the computation of the cost of equity.

Second, China is an anomaly in the sense that its rejection rate is the lowest of all of the countries (both developed and emerging). Moreover, the rejection rate remains below 5% in the two sub-periods. Comparing China to the other BRICs, we see that its rejection rates are generally lower, especially for the full period and the second sub-period. Hence, there seems to be something special about China. From the market integration section, we know that emerging markets are less integrated in general than developed markets. Although this argument applies for all emerging markets, and not just China, it is more relevant for China than for others for two reasons. First, many Chinese companies are not accessible to foreign investors, and second, these non-accessible companies are less integrated with world capital markets than the non-accessible companies of the other BRICs (Carrieri et al., 2013). For companies which are less integrated with the world market, the local index contains the most relevant information, resulting in low rejection rates [see Equation (5.8)].

Third, the zero rejection rate for Russia in the first sub-period is peculiar. However, we need to treat this percentage with care, because it is based on only 30 companies, for which firm-level stock returns were only available in 55% of the months on average.

Finally, comparing the rejection rates of the two 10-year sub-periods, we conclude that for eleven of the fifteen countries the rejection rate increases from the first to the second sub-period, while it decreases for four countries. This highlights the increasing importance of using the ICAPM instead of the local CAPM.[13]

5.5.2 Size of Difference in Cost of Equity

In the second part of this section, we want to assess the size of the difference in cost of equity when the local CAPM is used even though the ICAPM applies. To quantify

[13]The rejection rates for the full period are either in between the rates for the two sub-periods or higher than both. There are two dynamics at work here. On the one hand, combining the two sub-periods into one full period averages the rates over both sub-periods. On the other hand, the number of observations per company is higher for the full period than for individual sub-periods, leading to an increase in the power of the t-test. Hence, for countries where the rejection rate is higher for the full period than for the sub-periods, the latter effect is strongest, while for the others, the former effect dominates. This reasoning applies when the set of companies in the different time periods is the same. Since newly listed companies enter the set and delisted companies leave, the set changes. This explains how the rejection rate of South Korea and China for the full period could be lower than for either sub-period.

the size of the mistake at issue, we adopt Equation (5) of Stulz (1995) and inserted the parameter estimates for the betas [see Equations (5.2), (5.3) and (5.4)], which yielded the following equality:

$$\hat{R}_{i,G} - \hat{R}_{i,G,L} = \left(\hat{\beta}_{G,i} - \hat{\beta}_{L,i}\hat{\beta}_{G,L}\right)\left(E[R_G] - r_f\right), \tag{5.9}$$

where $E[R_G]$ is the expected return on the global index in U.S. dollars and r_f the riskless rate earned on U.S. T-bills. We use U.S. dollar returns and U.S. T-bills because we assume the perspective of a U.S. investor. In other words, $\mathrm{E}[R_G] - r_f$ is equal to the equity risk premium (ERP) of the global index in U.S. dollar returns.

Table 5.3 lists the *absolute* difference in cost of equity relative to the equity risk premium for each country when the local CAPM is used despite applicability of the ICAPM: in other words, the value from Equation (5.9) divided by the equity risk premium. We computed this relative difference in cost of equity for both "Reject" and "Non-reject" companies. Reject companies are the ones for which the difference in cost of equity is statistically significant, while Non-reject refers to companies for which this difference is insignificant (see Section 5.5.1).

Table 5.3. The absolute average difference in cost of equity relative to the global equity risk premium when the local CAPM is used even though the ICAPM applies. Results are presented per country. Companies for which the cost-of-equity difference was statistically different at the 5% level (i.e., designated as "Reject") were considered separately from companies for which the difference was insignificant (i.e., "Non-reject") (see Section 5.5.1). The countries and two categories are listed in the first column. The figures presented in the second column equal the value from Equation (5.9) divided by the global equity risk premium. We used the parameter estimates for the full period, 1996–2015. The unweighted average of all the countries is presented in the bottom rows.

Country	Difference
Australia	
Reject	41%
Non-reject	14%
Canada	
Reject	35%
Non-reject	17%
France	
Reject	27%
Non-reject	10%
Germany	
Reject	37%
Non-reject	14%
Japan	
Reject	27%
Non-reject	10%
The Netherlands	
Reject	35%
Non-reject	15%
Spain	
Reject	36%
Non-reject	13%
South Korea	
Reject	38%
Non-reject	15%
Switzerland	
Reject	27%
Non-reject	9.3%
United Kingdom	
Reject	37%
Non-reject	26%
United States	
Reject	15%
Non-reject	12%
Brazil	
Reject	33%
Non-reject	9.9%
Russia	
Reject	46%
Non-reject	19%
India	
Reject	33%
Non-reject	12%
China	
Reject	63%
Non-reject	22%
Average	
Reject	35%
Non-reject	15%

Not surprisingly, we see across the table that the difference in cost of equity is larger for reject than for non-reject companies. This difference is almost 2.5 times larger, on average, for the former group compared to the latter, as can be inferred from the final rows of the table.

To quantify the mistake in cost of equity when the local CAPM is used despite applicability of the ICAPM, the numbers in Table 5.3 must be multiplied by the equity risk premium (ERP). Table 5.4 contains ERPs for three different time periods; these have been taken from the Credit Suisse Global Investment Returns Yearbook 2016 (Credit Suisse, 2016, pg. 61), updating the data composed by Dimson, Marsh, and Staunton (2009).

Table 5.4. The equity risk premium (ERP) on the global market portfolio for a U.S. investor for three periods.

Period	ERP
1900–2015	4.2%
1966–2015	4.1%
2000–2015	2.0%

(Source: Credit Suisse Global Investment Returns Yearbook 2016 pg. 61)

Using the ERP for the 1900–2015 period, the average cost of equity is either under- or overestimated (because the values are absolute, we cannot distinguish between these cases in this analysis) by $35\% \times 4.20\% = 1.49\%$ for the reject companies and $15\% \times 4.20\% = 0.61\%$ for the non-reject companies. The overall under- or overestimation, that is, without taking the reject and non-reject companies into separate consideration, is equal to $18\% \times 4.20\% = 0.77\%$. Since this value is much closer to the value of the non-reject companies, this reflects the larger presence of non-reject companies in our sample. Note that our results indicate that at the company level, for example, there is a risk of over- or underinvestment due to under- or overestimation of the cost of equity.

Finally, we would like to compare our results for Nestlé with those of Stulz (1995). The difference in cost of equity between the ICAPM and the local CAPM [i.e., the value of Equation (5.9)] he reported for Nestlé was equal to –0.60%, while in our case it is equal to between –0.27% and –0.13%, depending on which risk premium from Table 5.4 we use. Moreover, this difference is not significantly different from zero. We therefore conclude that for Nestlé, the overestimation of riskiness has decreased in the last twenty years.[14] This implies, for this particular case, that when the local CAPM was used, the undervaluation of the stock price was lower than before. In addition, underinvestment due to an overestimation of the discount rate has become less of a concern.

5.5.3 Illustration of Difference in Cost of Equity

To illustrate the differences in cost of equity when the local CAPM is used despite ICAPM applicability, Figure 5.1 graphically depicts the direct and indirect betas per company for the 1996–2015 period. The results are presented per country.

Each dot in the graph represents a company. In cases where there is no difference in the cost of equity using the ICAPM versus the local CAPM the following equality [see Equation (5.6)] should hold:

$$\beta_{G,i} = \beta_{L,i}\beta_{G,L}.$$

In the figures, the x-coordinate is the estimate for the direct beta, $\hat{\beta}_{G,i}$, and the y-coordinate is the estimate for the indirect beta, $\hat{\beta}_{L,i}\hat{\beta}_{G,L}$. In general, a pricing error is small when a dot is close to the 45° line; conversely, the pricing error is large when a dot is far from the line.

[14] Even if we had used the risk premium of 6.22% that Stulz (1995) uses, the difference would be –0.40%, which is still lower than the difference reported in Stulz (1995).

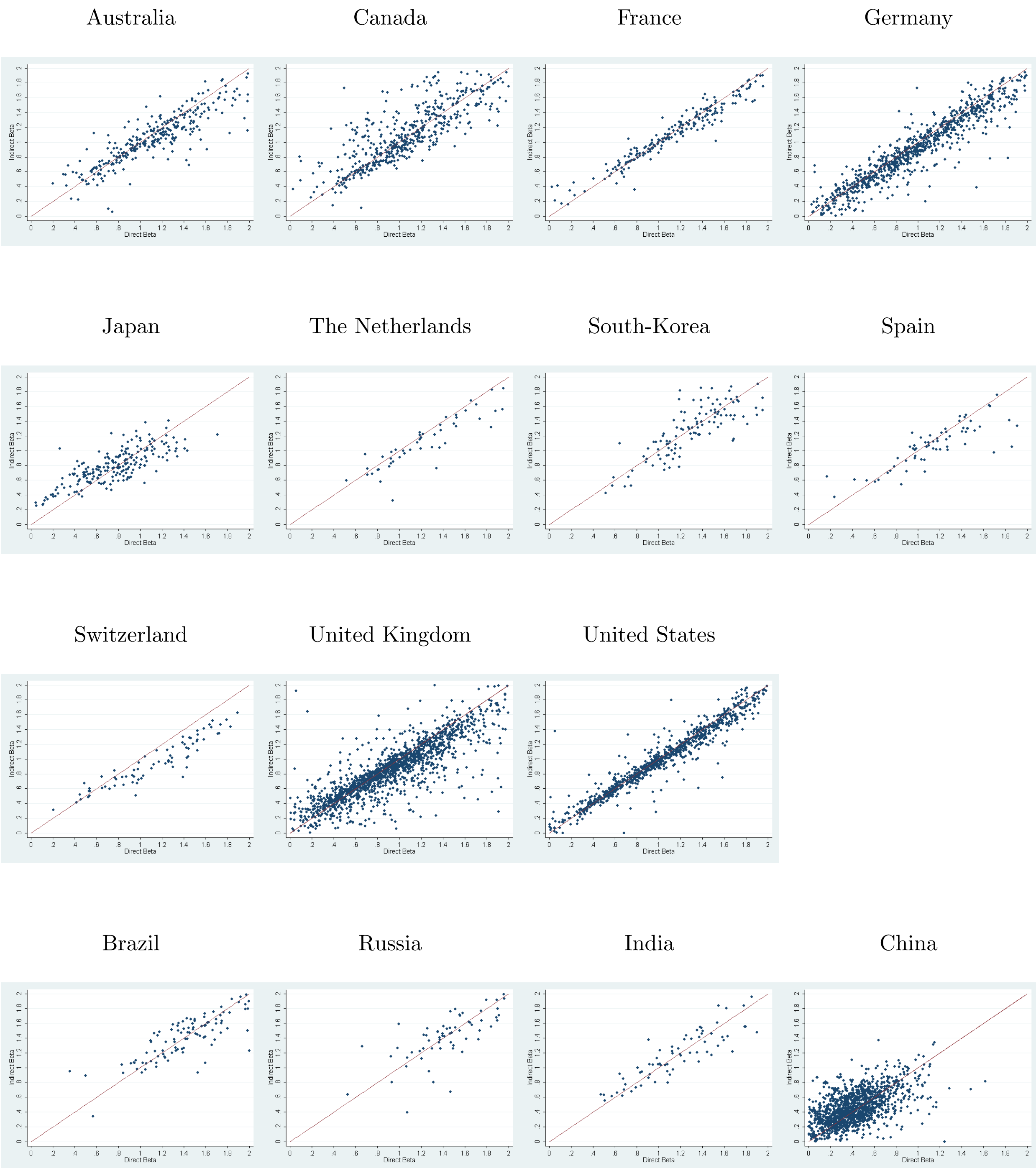

Figure 5.1. Graphical representation of the direct (x-axis) versus the indirect (y-axis) beta for the countries in our sample. The direct beta is the beta estimate obtained by regressing the company stock return on the global market return [Equation (5.2)]. The indirect beta is the product of the beta estimate obtained by regressing the company stock return on the local market return [Equation (5.3)] multiplied by the beta estimate obtained by regressing the local market return on the global market return [Equation (5.4)]. The graphs cover the 1996–2015 period.

Before discussing individual countries, we would like to first discuss how to interpret the graphs. Equation (11) of Stulz (1995) states that the market-value weighted-average difference in cost of equity when using the local CAPM versus the ICAPM equals zero. Note that this equality only holds when market indices include all stocks and their weight in the index is weighted with market value. Although the latter condition has been satisfied, since we only consider MSCI indices and those use market weighting, the former condition is violated, since not all stocks are included in the MSCI indices.

Nevertheless, this does not seem to result in large distortions in our sample, since the dots in the graphs are generally well situated around the 45° line. Differences in cost of equity may occur for individual stocks, however, as can be concluded from the large distance to the line for some of the dots. For these companies, a large error is introduced when the local CAPM is used instead of the ICAPM. The placement of the dots above or below the line determines whether the cost of equity is over- or underestimated. Dots situated below the line have a higher cost of equity when using the ICAPM versus the local CAPM. In other words, for this group, risk that is diversifiable locally is not diversifiable globally. Consider a firm whose return is uncorrelated with that part of the local market which is globally diversifiable. This leads to a low local beta, $\beta_{L,i}$. If, at the same time, the firm's return is strongly correlated with the world market, this results in a large global beta, $\beta_{G,i}$. The opposite holds for dots situated above the line: risk that is diversifiable globally is not diversifiable locally. Note that overestimation – dots above the line – leads to an undervaluation of the company or to underinvestment by the company. Conversely, underestimation – dots below the line – leads to overvaluation or overinvestment by the company.

To clarify the interpretation of the graph, we discuss the case of Switzerland. The companies listed in that country are almost exclusively located below the line. This implies an underestimation of the cost of equity when the local CAPM is used even though the ICAPM applies. In other words, these companies are exposed to risk that is diversifiable locally and not globally. Knowing that the market-value weighted-average of the differences for each country should be equal to zero, the subsample of Swiss firms we consider is not representative, because the companies are all below the line. Hence, the returns of Swiss firms in our sample are more correlated with the world market than with the local market. A possible explanation for this could be that these firms operate more globally. Moreover, from an investment perspective, the underestimation of the cost of equity for these Swiss sample companies suggests an overvaluation of their stock. Therefore, if an investor believes in the applicability of the ICAPM and expects market participants to adopt the same belief instead of them applying the local CAPM, they should short or underweight the Swiss sample companies in their portfolio.

Second, we look at the position of the dots along the 45° line. We focus first on Brazil and Russia, and then on China, because the dots in these graphs are more clustered near specific beta values. The Brazilian and Russian companies are congregated in the upper right corner, while Chinese companies are grouped in the lower left corner. To explain the position of the dots in these cases, we use a company's indirect beta. This is the product of the company's beta in relation to the local market multiplied by the local market's beta in relation to the global market. Assuming that we have a representative sample of companies for a country and that the local market *index* represents the local market, we know that the companies within a country have a weighted average beta that should be around one when the company return is regressed on the local index. In that case, the clustering of indirect betas in certain regions of the graph is due to a high or low beta for the local index in relation to the world index. This beta can be written as follows:

$$\beta_{G,L} = \frac{Cov[R_G, R_L]}{Var[R_G]} = \frac{\rho_{G,L} \cdot \sigma_L}{\sigma_G}, \tag{5.10}$$

where G and L denote global and local, respectively, and $\rho_{G,L}$ is the correlation between the return on the global and local index. Since the volatility, σ_G, of the global market is the same for all countries, high betas are a result of either high volatility in the local index or a high correlation between the local and the global market.

For Brazil and Russia, many of the dots are clustered in the upper right corner of the graph. In Brazil's case, this can be explained by a combination of a not-so-low correlation between the Brazilian market and the world market, at 0.72 (the average for all the countries is 0.76), and a relatively high local market volatility of 0.107 (the average for all the countries is 0.078). For Russia, the high volatility of the local market, by far the largest in the sample, at 0.159, explains the position of the Russian firms in the graph.

The volatility of the local Chinese market and the correlation between the local market and the world market are equal to 0.101 and 0.52, respectively. Inserting these numbers into Equation (5.10) produces a $\beta_{G,L}$ for China of 1.1, which is the ninth highest score of the fifteen countries we consider. Hence, this beta cannot explain the position of the dots in the bottom left corner because then we would have had a low beta. Recalling that the indirect beta is the product of $\beta_{G,L}$ and $\beta_{L,i}$, the explanation might be found in the latter. Using the same decomposition as in Equation (5.10), but now for $\beta_{L,i}$ yields:

$$\beta_{L,i} = \frac{\rho_{L,i} \cdot \sigma_i}{\sigma_L},$$

where $\rho_{L,i}$ is the correlation coefficient between the return of the local market and company i and σ_i the volatility of the return of company i. The average $\rho_{L,i}$ for the Chinese companies is 0.19, which is considerably less than the average of 0.53 for the rest of the countries (i.e., excluding China). Hence, the Chinese companies in our sample are much less correlated with their local market (i.e., the MSCI China indices). The explanation for this is that the Chinese sample companies are not well represented in the MSCI China indices.[15]

[15] At first, we wanted to collect sample companies for all countries using the constituents of the local MSCI indices. Since we did not have access to these constituents, however, we relied on the constituents of other well-known local indices, e.g., in the case of China, the Shanghai Stock Exchange (SSE) (see Appendix B).

5.6 Robustness

Up until this point, we have only used the CAPM, that is, we have only used the market index as a regressor. We now want to extend this model to include the other Fama and French (1993) factors, to wit, High Minus Low (HML) and Small Minus Big (SMB). Before presenting those results, we must first generalize the derivation from Section 5.3 to this setting. The ICAPM, Equation (5.2), then changes to

$$R_i = \alpha_{G,i} + Z_G\beta_{G,i} + \varepsilon_{G,i}, \tag{5.11}$$

where Z_G consists of the *global* Fama-French factors (R_G, HML_G, and SMB_G, respectively), $\beta_{G,i}$ contains the corresponding global factor coefficients, and $\varepsilon_{G,i}$ has mean zero and is orthogonal to Z_G.

Analogously, the local CAPM, Equation (5.3), becomes

$$R_i = \alpha_{L,i} + Z_L\beta_{L,i} + \varepsilon_{L,i}, \tag{5.12}$$

where Z_L contains the *local* Fama-French factors (R_L, HML_L, and SMB_L, respectively), $\beta_{L,i}$ consists of the corresponding local factor coefficients, and $\varepsilon_{L,i}$ has mean zero and is orthogonal to Z_L.

We note that the ICAPM model should also hold for the return on the local index, R_L, that is,

$$R_L = \alpha_{G,L} + Z_G\beta_{G,L} + \varepsilon_{G,L}. \tag{5.13}$$

Inserting this expression into Equation (5.12) and replacing Z_G and Z_L by their components (i.e., the global and local Fama-French factors) yields:

$$\begin{aligned} R_i =& \alpha_{L,i} + \beta_{L,i,1}\left(\alpha_{G,L} + \beta_{G,L,1}R_G + \beta_{G,L,2}HML_G + \beta_{G,L,3}SMB_G + \varepsilon_{G,L}\right) \\ &+ \beta_{L,i,2}HML_L + \beta_{L,i,3}SMB_L + \varepsilon_{L,i} \\ =& \alpha_{L,i} + \beta_{L,i,1}\alpha_{G,L} + \beta_{L,i,1}\beta_{G,L,1}R_G + \beta_{L,i,1}\beta_{G,L,2}HML_G + \beta_{L,i,1}\beta_{G,L,3}SMB_G \\ &+ \beta_{L,i,2}HML_L + \beta_{L,i,3}SMB_L + \beta_{L,i,1}\varepsilon_{G,L} + \varepsilon_{L,i}, \end{aligned} \tag{5.14}$$

where $\beta_{G,L,1}$, for example, indicates the coefficient corresponding to the first regressor, R_G, of Equation (5.13) and $\beta_{L,i,1}$, for instance, the coefficient corresponding to the first regressor of Equation (5.12), R_L.

When the model presented in Equation (5.11) holds, $\varepsilon_{G,L}$ is orthogonal to Z_G and Equations (5.11) and (5.14) are equivalent if and only if local idiosyncratic risk, $\varepsilon_{L,i}$, is orthogonal to the global factors, Z_G, and $\beta_{L,i,2}$ and $\beta_{L,i,3}$ are equal to zero. To test whether $\varepsilon_{L,i}$ is orthogonal to the global factors, we consider the following equation:

$$\varepsilon_{L,i} = Z_G\kappa_i + \eta_i, \tag{5.15}$$

where η_i has mean zero and is orthogonal to Z_G and Z_L.

Inserting Equation (5.15) into (5.12) then yields the generalization of Equation (5.8):

$$R_i = \alpha_{L,i} + Z_L\beta_{L,i} + Z_G\kappa_i + \eta_i.$$

Finally, we then apply an F-test per company to test whether

$$\beta_{L,i,2} = \beta_{L,i,3} = \kappa_{i,1} = \kappa_{i,2} = \kappa_{i,3} = 0, \tag{5.16}$$

where $\kappa_{i,1}$, for example, represents the first coefficient of the coefficient vector κ_i. When either of these coefficients differs significantly from zero, the cost of equity using the global model differs significantly from the cost of equity using the local model.

We performed this analysis for the full period, 1996–2015, for the countries for which the local Fama-French factors were available on the website of Kenneth French (`http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/`). The global SMB and HML are also obtained from his source. The results are presented in Table 5.5.

Table 5.5. The percentage of rejection compared to the total number of companies in our sample per country for the full time period for the global pricing model when we include Fama-French factors. Rejection occurs when one of the coefficients of Equation (5.16) is significantly (at the 5% level) different from zero. An F-test is applied to test this hypothesis.

	1996–2015
Canada	26%
France	17%
Germany	10%
The Netherlands	28%
Spain	28%
Switzerland	51%
United Kingdom	22%
United States	21%

Comparing these results with the results for the ICAPM presented in Table 5.2, the only decrease evident is for Switzerland, while the rejection rate for Germany remains equal. For the remaining six countries, there is an increase in rejection rates. In short, we conclude that adding Fama-French factors most often increases the likelihood of rejection.

5.7 Conclusion

In this chapter, we reassessed the cost of equity in international capital markets. We determined that for the 1996–2015 period, the error introduced when a local CAPM is used even though the ICAPM applies is, on average, equal to 0.77 percentage points. In terms of the historical global market risk premiums, this represents 18%. In addition to this economic significance, we document statistical significance for 19% of the companies; that is, for these companies the mistake is statistically distinct from zero. When we restrict the sample to companies for which the difference is statistically different from zero, the error jumps to 1.49 percentage points, thereby representing 35% of the historical risk premium. Therefore, applying the local CAPM instead of the ICAPM can lead to considerable mistakes in the cost of equity.

We discussed two implications of wrongly estimating the cost of equity: the valuation of the company and the decision to invest. Firstly, overestimation of the cost of equity implies that the rate by which dividends are discounted to arrive at the stock price will be too high. The company will thus be undervalued. The opposite holds true for an underestimation of the cost of equity. Secondly, underestimation might lead a company to overinvest, since it wrongly believes that projects are profitable enough when in reality they are not. Again, conversely, overestimation leads to underinvestment.

Among the countries we consider, China presents a special case. The difference in the cost of equity between the two models is significant for only 1.9% of the Chinese companies in the full sample. We ascribe this to a lack of integration on the part of the small Chinese companies we consider. The results for the other BRICs are more in line with those of the developed countries.

When we extended the model with Fama-French factors, the rejection rates increased slightly for the majority of the countries. We therefore conclude that our results are robust for this more general specification.

Appendix

A. Methodology

A.1 CAPM Regressions

Start from the global CAPM (ICAPM) in excess returns:

$$E[R_i] = \alpha_{G,i} + \beta_{G,i} E[R_G], \tag{A.1}$$

$$\beta_{G,i} = \frac{Cov[R_i, R_G]}{Var[R_G]},$$

$$\alpha_{G,i} = 0. \tag{A.2}$$

Let realised returns be

$$R_i = E[R_i] + u_i, \tag{A.3}$$

$$R_G = E[R_G] + u_G, \tag{A.4}$$

with u_i and u_G be truly unpredictable innovations. Note that this implies that we can also write

$$\beta_{G,i} = \frac{Cov[u_i, u_G]}{Var[u_G]}.$$

Now consider the regression

$$R_i = \alpha_{G,i} + \beta_{G,i} R_G + \varepsilon_{G,i}. \tag{A.5}$$

Inserting (A.3) and (A.4) into (A.5), and using (A.1) and (A.2), it then follows, after rearranging, that

$$\varepsilon_{G,i} = u_i - \beta_{G,i} u_G, \tag{A.6}$$

which we use to show the validity of the OLS-estimator for Equation (5.2):

$$\begin{aligned} Cov\left[\varepsilon_{G,i}, R_G\right] &= Cov\left[u_i - \beta_{G,i} u_G, u_G\right] \\ &= Cov\left[u_i, u_G\right] - \beta_{G,i} Cov\left[u_G, u_G\right] \\ &= Cov\left[u_i, u_G\right] - \frac{Cov\left[u_i, u_G\right]}{Var\left[u_G\right]} Var\left[u_G\right] \\ &= 0. \end{aligned}$$

Note that if the ICAPM does *not* hold, this implies that alpha is not equal to zero. The model still assumes that beta is driving the expected returns, so we still have that the residual is orthogonal to the regressor in Equation (A.5).

A.2 Global Versus Local CAPM

The ICAPM also implies for country L:

$$E\left[R_L\right] = \alpha_{G,L} + \beta_{G,L} E\left[R_G\right], \tag{A.7}$$

with the same implications for the regression as above, and $\alpha_{G,L} = 0$.

The local CAPM on the other hand implies:

$$E\left[R_i\right] = \alpha_{L,i} + \beta_{L,i} E\left[R_L\right], \tag{A.8}$$

also with the same implications for the accompanying regression, and $\alpha_{L,i} = 0$.

Similar to above, note that if either the ICAPM or the local CAPM does *not* hold, this implies that the alphas are not equal to zero. The models still assume that betas are driving the expected returns, so we still have that in each regression the residual is orthogonal to the regressor [in the regressions from Equations (A.7) and (A.8)].

Next, consider a regression of R_i on R_L and R_G, assuming the ICAPM is valid (i.e., Equations (A.1) and (A.7) hold):

$$R_i = \alpha_i + \gamma_{L,i} R_L + \gamma_{G,i} R_G + \eta_i. \tag{A.9}$$

Using $R = E[R] + u$, we have that

$$\eta_i = u_i - \gamma_{L,i} u_L - \gamma_{G,i} u_G, \tag{A.10}$$

which is similar to Equation (A.6). To simplify, denote

$$\begin{aligned}
&y = R_i, \alpha = \alpha_i, \eta = \eta_i, e = u_i,\\
&\gamma' = \begin{pmatrix} \gamma_{L,i} & \gamma_{G,i} \end{pmatrix},\\
&x' = \begin{pmatrix} R_L & R_G \end{pmatrix},\\
&u' = \begin{pmatrix} u_L & u_G \end{pmatrix}.
\end{aligned}$$

So, Equations (A.9) and (A.10) can be written as

$$\begin{aligned}
&y = \alpha + \gamma' x + \eta,\\
&\eta = e - \gamma' u.
\end{aligned}$$

To check for orthogonality between the residual and the regressors in Equation (5.8):

$$\begin{aligned}
Cov\left[\eta_i, \begin{pmatrix} R_L \\ R_G \end{pmatrix}\right] &= Cov[\eta, x] = Cov[e - \gamma' u, u] = \Sigma_{eu} - \gamma' \Sigma_{uu}\\
&= \Sigma_{eu} - \Sigma_{eu}\Sigma_{uu}^{-1}\Sigma_{uu} = \Sigma_{eu} - \Sigma_{eu} = 0.
\end{aligned}$$

B. Data Sources

Table B.1. Data types and data sources per country. Column 2 lists the indices from which the constituents from 1980 to 2015 were selected as the stocks in our sample. Stock prices are from Datastream. Exchange rates (Column 4) are either from FRED or Datastream. The corresponding Datastream code is listed in Column 5. Local market indices are the national MSCI market indices, and the global index is the World MSCI index. The prices for all MSCI indices were obtained from Datastream.

Country	Stock prices		Exchange Rate		Local Market Index		Global Market Index	
	Index	Source	Source	Datastream Code	Index	Datastream Code	Index	Datastream Code
Australia	ASX					MSAUSTL		
Canada	TSX					MSCNDAL		
France	SBF 120					MSFRNCL		
Germany	CDAX					MSGERML		
Japan	NIKKEI 225					MSJPANL		
Netherlands	AEX					MSNETHL		
Spain	IBEX 35	Datastream			MSCI	MSSPANL	World MSCI	TOTMKWD
South Korea	KOSPI 200					MSKOREL		
Switzerland	SIP					MSSWITL		
U.K.	FTSE All					MSUTDKL		
U.S.	S&P 500					MSUSAML		
Brazil	BOVESPA					MSBRAZL		
Russia	RTS		Datastream	CISRUB$		MSRUSSL		
India	CNX NIFTY					MSINDIL		
China	SSE Composite		FRED			MSCHINL		

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